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Keywords
Health, Job Tasks, Working Conditions, MET

JEL Codes
I1, I14, I18, J24, J28

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The Health Burden of Job Strain: Evidence from Europe

Petru Crudu* and Giacomo Pasini†

Abstract

This study examines the impact of occupational stressors and tasks throughout an individual's career on their health in older age. Leveraging comprehensive job occupation data from the SHARE dataset, we establish precise connections between stressors and specific jobs at the 4-digit ISCO code level. To ensure accurate measurement of physical exertion, we propose the use of Metabolic Equivalent of Task (MET) based on the metabolic rate consumption associated with each task. Our study makes two key contributions. First, we provide compelling evidence that individuals, especially women, engaged in physically demanding jobs experience significantly worse health in older age. Our results remain valid after conducting several robustness checks and after controlling for a rich set of variables. Secondly, we introduce a novel methodology to identify harmful tasks and measure overall Job Strain Intensity, which also incorporates unobserved occupational stressors. This approach allows us to pinpoint specific harmful tasks and 4-digit ISCO codes, providing valuable insights for targeted retirement schemes and addressing important considerations regarding the fairness of statutory retirement ages. Additionally, policymakers can benefit from our findings to foster healthier work environments and guide investments towards automating high-risk tasks, thereby improving overall workplace safety and well-being.

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1 Introduction

Nowadays, the time spent at work is one of the most time-consuming activities in our entire life, constituting approximately 26% of our adulthood lifespan[1]. Due to the considerable amount of time spent at work and the inherent nature of job demands, which are often beyond the control of workers, working conditions emerge as a highly influential factor in shaping the health and overall well-being of individuals. Despite the significance of this topic, the economics literature neglects the impact of work environments and tasks on individual outcomes.

This work investigates the impact of on-the-job occupational stressors and tasks performed during the entire career on older workers' health. The key novelty lies in our ability to observe job occupations throughout an individual's entire career at a highly detailed level. The SHARE data (Brugiavini et al. (2019)) allows us to access the 4-digit ISCO code for European individuals aged 50 and above, providing a comprehensive record of all the job episodes they have experienced in their lives. This level of detail enables us to precisely link occupational stressors to each job. To measure physical expenditures accurately, we propose using the Metabolic Equivalent of Task (MET) (Deyaert et al. (2017)). This method calculates the physical activity energy expenditure based on the metabolic rate associated with each task identified by the 4-digit ISCO code. Furthermore, we can delve into other job demands at a granular level. For instance, we can examine exposure to psychosocial and carcinogenic agents (Kroll (2015)) and assess task routines (Mihaylov and Tijdens (2019)).

From an empirical point of view, our study makes two significant contributions. Firstly, it offers empirical evidence on the impact of occupational stressors on Self-perceived poor health. Secondly, it introduces a novel methodology for identifying the most harmful tasks and measuring the overall Job Intensity Strain. This innovative approach accounts for unobservable components that are typically more challenging to capture.

To identify the effect of occupational stressors on health, we rely on a rich set of controls that tackle all the sources of endogeneity. Specifically, we have detailed information on childhood conditions, current socio-economic conditions, job characteristics, healthy habits, and health-protecting behaviours. The results show that individuals performing more physically demanding jobs are experiencing significantly worse health during older

[1]The 26% is related to the adulthood time of an average citizen in the European Union. This calculation takes into account several factors. Firstly, the expected duration of working life in the European Union surpasses 36.5 years, as reported by Eurostat (Eurostat (2022)). Additionally, the average weekly working hours in the region amount to approximately 36.2 hours (Eurostat (2021)). For the purpose of this estimation, only the period from 20 to 65 years of age is considered adulthood, and it assumes an average of 8 hours of sleep per night.

ages. For instance, the transition from a job with relatively lower physical demands, like "Dental assistant and therapist," to a more physically strenuous job, such as "Hand packer," results in an effect equivalent to ageing by 2.33 additional years in terms of health impact. Furthermore, we observe an interesting gender heterogeneity, with women being more affected than men. No relevant effects are detected for the other occupational stressors. The results of our analysis remain robust even after subjecting them to rigorous robustness checks. We have employed alternative health dimensions and various methods, including Oster bounds (Oster (2019)), Shapley values (Roth (1988)), and the Causal Forest estimator (Athey et al. (2019)), to verify the stability and reliability of our findings.

In the second part of the paper, we present a novel methodology based on the LASSO (Least Absolute Shrinkage and Selection Operator) (Tibshirani (1996)) and the granular task data for each 4-digit ISCO code. This approach allows us to identify the most detrimental tasks from a sparse matrix of standardised tasks. By doing so, we can pinpoint the specific tasks that are strongly associated with poorer health outcomes. Additionally, we construct a new measure called Job Strain Intensity, which quantifies the proportion of harmful tasks out of all tasks performed within each 4-digit ISCO code. Notably, this innovative measure comprehensively captures the overall job strain, encompassing the impact of unobservable heterogeneity that traditional indexes often struggle to capture. This second part of the study is particularly noteworthy. It confirms the robustness of the relationship between MET and health, even after controlling for the Job Strain Intensity. Additionally, it enables us to discern the most harmful tasks and 4-digit ISCO codes that are most likely linked to adverse health outcomes. For instance, the top five harmful tasks identified are "Construction and restoration," "Preparing, cooking, serving meals," "Sweeping, vacuum-cleaning, polishing and washing," "Repair/maintenance," and "Operating heavy-duty equipment."

In conclusion, this study presents compelling evidence of the adverse effects of physically demanding occupations throughout one's lifetime on old-age health. Additionally, the research offers practical guidelines to address current challenges. The novel methodology identifies specific tasks and 4-digit ISCO codes, which can guide the development of targeted retirement schemes for individuals more likely to face shorter life expectancy and disability-free life years due to their occupational history. This targeted approach addresses concerns raised in recent literature regarding the fairness of a general increase in statutory retirement ages (Deeg et al. (2021) Lozano and Solé-Auró (2021) Anders et al. (2022)). Moreover, the identification of specific tasks and job codes can aid policymakers and employers in refining safety regulations in workplaces and directing investments towards automating the most harmful tasks.

2 Litearature

This work contributes to different strands of literature.

The first line of literature investigates the impact of occupational stressors on health. Specifically, the body of literature concerning the relationship between physical activity (PA) and health is extensive, however, it remains inconclusive. On the one hand, there is considerable agreement that physical activity during leisure time improves overall health. For instance, Moore et al. (2012) investigates the combined findings of six cohort studies (one Swedish study and five studies conducted in the United States) which involve a sample size of almost 650,000 individuals. The study shows the vital importance of leisure physical activity for human health, highlighting its role in weight management, prevention or delay of heart disease, type 2 diabetes, and cancers. Additionally, engaging in physical activity improves individuals' well-being and increases their life expectancy. Specifically, surpassing the recommended minimum of 150 minutes of brisk walking per week is linked to a substantial increase in life expectancy, ranging from 3.4 to 4.5 years (WHO et al. (2020)). On the other hand, the impact of occupational physical activity on health is still ambiguous. Samitz et al. (2011) rely on a comprehensive meta-analysis to point out that various domains of physical activity (including the occupational PA) decrease all-cause mortality. Specifically, the study found that the largest risk reduction per unit of time increase was observed for vigorous exercise. Moderate-intensity activities of daily living were also found to have a beneficial, albeit comparatively lesser, effect on reducing mortality. Again, Cillekens et al. (2022) show within a systematical review with a meta-analysis that occupational physical activity is not statistically associated with cardiovascular disease mortality. On the opposite, according to McEwen (2000), prolonged exposure to cumulative strain leads to physiological damage known as allostatic load. Consequently, long-term on-the-job physical stressors can expedite the progression of the disease. This mechanism primarily arises from disruptions in hormonal levels that impede the optimal functioning of both the brain and immune system. Additionally, medical studies that placed emphasis on long-term follow-up studies show a statistically significant association between physical demands and cardiovascular morbidity and mortality. For example, the Copenhagen Male Study conducted a 30-year follow-up (Holtermann et al. (2010)), revealing that high physical work demands contribute to increased cardiovascular mortality among non-fit men. Similarly, the Kuopio Ischemic Heart Disease Risk Factor Study, which followed Finnish middle-aged working men for 20 years, established a positive association between occupational energy expenditure and the occurrence of acute myocardial infarction (Krause et al. (2015)). Again, according to Holtermann et al. (2018), tasks performed on the job imply different intrinsic features with respect to leisure time activities. In detail, leisure time physical activities are voluntarily performed with short duration and adequate healing time, whereas on-the-job tasks may entail static loading, heavy lifting, repetitive and poorly ergonomic postures, and longer periods with little recovery time. As a result, the on-the-job benefits of physical activity might be overwhelmed by the unavoidable costs to perform the tasks.

The medical literature provides ambiguous evidence about the relationship between on-the-job physical expenditure and health. Furthermore, it focuses mainly on pure associations overlooking endogenous factors. Despite the relevance of the topic, there is limited evidence in the economic literature regarding the impact of on-the-job physical expenditure on health. For instance, (Case and Deaton (2005)) utilize data from the National Health Interview Survey (NHIS) spanning the years 1986 to 2001 to document that blue-collar workers exhibit poorer self-assessed health outcomes in comparison to white-collar workers. Moreover, they highlight that the deterioration in health is more rapid for manual workers approaching retirement age. Besides, Fletcher et al. (2011) investigate the impact of job characteristics, specifically physical demands on individual health using the Panel Study of Income Dynamics dataset (PSID). The study utilises five-year cumulative measures of these job characteristics to align with findings from the biological and physiological literature, which suggest that prolonged exposure to hazards and stresses negatively affects health. In order to mitigate potential self-selection biases, Fletcher et al. (2011) incorporate lagged health measures and a comprehensive set of pre-determined characteristics into their analysis. They find that working in jobs characterized by adverse conditions leads to a reduction in health. Additionally, they highlight that the impact of these conditions on health is more pronounced for women. Furthermore, their research suggests that higher earnings may serve as a protective factor against health shocks. Next, Ravesteijn et al. (2018) expanses the analysis using the German Socioeconomic Panel (SOEP). They use a dynamic model that takes into account factors influencing both health outcomes and occupational selection, the study finds that selection into specific occupations explains at least 60% of the observed association. Furthermore, the detrimental effects of occupational characteristics such as physical strain and low job control become more pronounced with age. For individuals in the late stages of their careers, exposure to one year of high physical strain is equivalent to the health decline typically associated with ageing for 16 months.

Again, Belloni et al. (2019) investigates the effect of specific job characteristics and working conditions on older workers' physical and mental health by making use of SHARE data. They claim that physical environment and work intensity emerge as noteworthy predictors of overall health, whereas low job security and uncertain career prospects exhibit significant associations with affective or emotional disorders. They conclude by suggesting that policymakers should take into account the potential negative health implications of prolonged workforce participation, particularly in occupations characterized by substandard job quality. Consequently, any decision to raise the legal retirement age should be accompanied by policies that provide support to the most vulnerable workers and prioritize job improvement initiatives.

3 Data

3.1 SHARE data

SHARE, the Survey of Health, Ageing and Retirement in Europe, is a representative longitudinal survey for people aged 50 or older from 28 European countries and Israel that started in 2004. In detail, we use data from the Job Episode Panel (Brugiavini et al. (2019)) and wave 7 specifically (Börsch-Supan (2019)) to construct a retrospective long panel containing detailed information about each respondent throughout her/his life. The sample contains 39,529 unique individuals for which is available information for at least one job occupation. Table 1 shows the country distribution.

Country	Freq.	Percent	Country	Freq.	Percent
Austria	1927	4.87	Hungary	727	1.84
Germany	2283	5.78	Portugal	639	1.62
Sweden	1599	4.05	Slovenia	2412	6.10
Spain	1994	5.04	Estonia	3023	7.65
Italy	1775	4.49	Croatia	1646	4.16
France	1418	3.59	Lithuania	1119	2.83
Denmark	1319	3.34	Bulgaria	1462	3.70
Greece	493	1.25	Cyprus	430	1.09
Switzerland	1165	2.95	Finland	1248	3.16
Belgium	2137	5.41	Latvia	704	1.78
Israel	1069	2.70	Malta	569	1.44
Czech Republic	2500	6.32	Romania	970	2.45
Poland	2418	6.12	Slovakia	1576	3.99
Luxembourg	907	2.29	Total	39529	100.00

Table 1: Frequency by country.

3.1.1 Health outcomes

SHARE microdata provides several health outcomes measured during older ages. As the main outcome variable, we rely on Self-perceived poor health (Sphus), measured on a Likert scale where 1 is "Excellent" and 5 is "Poor". Table 2 shows the descriptive statistics of "Self-perceived poor health" and additional health outcomes used as robustness checks of the main results.

Next, SHARE provides information about a very large set of physical illnesses ever experienced at least once in life. This allows a better understanding of which are the diseases through which health is impacted. The following diseases are coded as dummy variables: Heart attack, Hypertension, Cholesterol, Stroke, Diabetes, Lung, Cancer, Stomach, Parkinson, Cataracts, Hip fractures, Other fractures, Alzheimer, Emotional disorders, Rheumatoid arthritis, Osteoarthritis, Kidney.

Health outcome	Obs	Mean	Std. dev.	Min	Max
Self-perceived poor health	39529	3.23	1.04	1	5
ADL	39529	0.18	0.74	0	6
IADL	39529	0.34	1.15	0	9
Limitations with activities	39529	0.46	0.50	0	1
Mobility limitations	39529	1.47	2.19	0	10
Max grip strength	36612	34.13	11.43	1	95
N chronic diseases	39529	1.79	1.60	0	12
BMI	39529	27.39	4.76	13	74
Disability injury	39479	0.10	0.31	0	1
Health limits work	35045	0.24	0.43	0	1
Disease					
Heart attack	39414	0.24	0.43	0	1
Hypertension	39414	0.04	0.20	0	1
Cholesterol	39414	0.13	0.34	0	1
Stroke	39414	0.05	0.23	0	1
Diabetes	39414	0.05	0.23	0	1
Lung	39414	0.04	0.21	0	1
Cancer	39414	0.00	0.09	0	1
Stomach	39414	0.07	0.26	0	1
Parkinson	39414	0.01	0.13	0	1
Cataracts	39414	0.05	0.24	0	1
Hip fractures	39414	0.01	0.12	0	1
Other fractures	39414	0.07	0.26	0	1
Alzheimer	39414	0.09	0.30	0	1
Emotional disorders	39414	0.18	0.39	0	1
Rheumatoid arthritis	39414	0.02	0.16	0	1
Osteoarthritis	39414	0.07	0.26	0	1
Kidney	39414	0.09	0.30	0	1

Table 2: Descriptive statistic of health outcomes and diseases.

3.1.2 Occupations

To define the occupational titles we employ the International Standard Classification of Occupations of the Organisation for Economic Co-operation and Development (OECD; ISCO-08)[2]. ISCO-08 is a tool for categorizing jobs into a series of groups that are defined in accordance with the tasks and responsibilities performed in the work. This categorization eases international comparability. ISCO-08 classifies jobs following four hierarchical levels. The broader level contains 10 ”Major groups” in which similar jobs are aggregated according to the skills required for the jobs and then ranked from ”1 Managers” and ending with ”9 Elementary occupations”[3]. Next, the major groups are first split into 43 sub-major groups (2-digit codes) and again into 130 minor groups (3-digit codes). Finally, occupations are categorized into 436 unit groups (4-digit codes). By construction, the heterogeneity in skills and tasks between major groups is straightforward. However, the diversity of skills and tasks exist also within the same major group. Table 23 shows the categorization of the ”9 Elementary occupations” major group that suggests huge heterogeneity in job duties also within the same major group (e.g., ”9211 Crop Farm Labourers” vs ”9411 Fast Food Preparers”).

	Frequency	Percent	Sphus (Mean)
0-Armed forces occupations	48	0.12	3.90
1-Managers	1760	4.74	3.07
2-Professionals	6478	17.45	2.99
3-Technicians and associate professionals	4634	12.48	3.13
4-Clerical support workers	4107	11.06	3.09
5-Service and sales workers	5291	14.25	3.22
6-Skilled agricultural, forestry and fishery workers	1585	4.27	3.52
7-Craft and related trades workers	6697	18.04	3.34
8-Plant and machine operators, and assemblers	3270	8.81	3.40
9-Elementary occupations	3258	8.78	3.47
Total	37128	100.00	

Table 3: Descriptives according to the 1-digit ISCO code occupation.

Table 3 presents the distribution of major occupational groups in the sample along with the corresponding mean and standard deviation of Self-perceived poor health. Among the various categories, ”Craft and related trades workers” emerges as the most populous group, comprising nearly 20% of the total interviewees. In contrast, ”Armed forces occupations” exhibit minimal representation in the data. As expected, the analysis reveals

[2]https://www.ilo.org/public/english/bureau/stat/isco/isco08/index.htm
[3]The tenth category contains the ”Armed forces occupations”.

that individuals in the "Managers" and "Professionals" categories tend to report better overall health. Conversely, those employed in "Elementary occupations" are more likely to report poorer health status.

3.1.3 Occupational stressors

Jobs encompass a variety of multidimensional occupational stressors. To accurately evaluate the influence of physical expenditure, it is crucial to account for other simultaneous stressors. Specifically, apart from physical expenditure, we consider additional measures of occupational stressors at the 4-digit ISCO code level. These measures include psychosocial stress, exposure to carcinogenic agents, and the nature of the job routine

First, the physical activity required on the job tasks is recovered from Deyaert et al. (2017). They encode the physical activity energy expenditures by means of Metabolic Equivalent of Task (METs). The MET values convey the ratio of the work metabolic rate to the standard resting metabolic rate and thus indicate how physically demanding an activity is in comparison to a condition at rest. Specifically, the energy cost of sitting quietly is 1 MET, whereas, walking at a very low speed in the office costs an energy equivalent of 2 METs. For instance, table 4 shows that "University and higher education teachers" (ISCO-08 code 2310) have an average of 1.58 METs. Again, table 4 can be insightful on how this measure is determined. First, for each ISCO code are retrieved the job-specific tasks from the ISCO classification document ILO (2012). Then, for each task are recovered the physical activity energy expenditures from the standardized list of activities in Ainsworth et al. (2011) Compendium[4]. Finally, the physical activity energy expenditure for each 4-digit ISCO code is averaged over the job-specific tasks.

This approach enables a comprehensive understanding of the lifetime physical strain encountered at work by each individual, largely surpassing the level of detail found in prior literature. Furthermore, since the METs are retrieved from an external source, they do not relate to the self-reported outcome measures.

[4]The MET values in the Compendium are applicable to healthy, able-bodied adults between the ages of 18 and 65, but they are unable to calculate the precise energy cost of physical activities for individuals according to body mass, adiposity, age, gender, movement efficiency, and the working environment in which the activities were performed.

Task	Task Abbreviation	Compendium Code and Label	MET Value
(a) Designing and modifying curricula and preparing courses of study in accordance with requirements	Designing curriculum, lessons and activities	9060 'sitting, studying, general, including reading and/or writing, light effort'	1.3
(b) Preparing and delivering lectures and conducting tutorials, seminars and laboratory experiments	Delivering lectures	11,791 'walking on job, less than 2.0 mph, very slow speed, in office or lab area'	2
(c) Stimulating discussion and independent thought among students	Stimulating discussion	11,791 'walking on job, less than 2.0 mph, very slow speed, in office or lab area'	2
(d) Supervising, where appropriate, experimental and practical work undertaken by students	Supervising of students, staff and colleagues	11,791 'walking on job, less than 2.0 mph, very slow speed, in office or lab area'	2
(e) Administering, evaluating and marking examination papers and tests	Marking papers and tests	9040 'sitting, writing, desk work, typing'	1.3
(f) Directing research of post-graduate students or other members of department	Directing and participating in research	11,585 'sitting meetings, light effort, general, and/or with talking involved'	1.5
(g) Researching into and developing concepts, theories and operational methods for application in industrial and other fields	Desk based research	9040 'sitting, writing, desk work, typing'	1.3
(h) Preparing scholarly books, papers or articles	Preparing papers	9040 'sitting, writing, desk work, typing'	1.3
(i) Participating in departmental and faculty meetings and in conferences and seminars	Meetings	11,585 'sitting meetings, light effort, general, and/or with talking involved'	1.5

Table 4: Job-specific tasks from the ISCO-08 job classification for "University and higher education teachers" (ISCO-08 code: 2310).

Further, we rely on the Job Exposure Matrix (JEM) developed by Kroll (2015) to control for psychosocial stress and carcinogenic agents exposure in the workplace. The JEM is derived from a large-scale representative survey conducted in 2006 by the German Federal Institute for Vocational Education and Training (BIBB). In detail, the psychosocial stress metric (1 to 10) combines information regarding mental stress (overwhelmed, disappointed, low fault tolerance at work), social pressure (conflicts with colleagues or superiors, lack of control options), and time pressure (time pressure, shifts, excessively long working hours). Similarly, the carcinogenic agents' exposure metric (1 to 10) determines the decile of each 4-digit ISCO code job to the exposure to toxins, gases, and climatic stress.

Another important dimension to take into account is the routine of the job-specific tasks. As a matter of fact, the repetition of manual tasks in poor ergonomic conditions may influence health regardless of the required physical effort. Similarly, easy repetitive cognitive tasks may impact mental health. Mihaylov and Tijdens (2019) allows assigning to each 4-digit ISCO code both the manual and cognitive routine of the tasks. They start from the ISCO classification that comprises a total of 3,264 tasks, which are categorized as either manual or cognitive routines, depending on their susceptibility to replacement by computer-controlled technology. Subsequently, the shares of manual and cognitive routine tasks are calculated for each specific 4-digit ISCO occupation.

An important data limitation relates to the fact that all the above-mentioned occupational stressors are valid for the first decade of 2000. Automation and other time changes might have influenced the occupational stressors required for any job.

3.1.4 Other control variables

However, ignoring other individual characteristics might spuriously associate occupational stressors with health.

Family background plays a significant role as an indicator of lifetime outcomes (Currie (2009); Case et al. (2002, 2005)). In order to account for this mechanism, we utilise a range of retrospectively asked questions that capture childhood conditions between the ages of 10-15. These questions help to control for the influence of family background on the variables under consideration. Firstly, we consider the occupation of the family's breadwinner and attach the METs (Metabolic Equivalent of Tasks) of their job to account for the intergenerational transmission of job-related stressors. Additionally, we assess the socioeconomic status during childhood by examining variables such as the number of rooms at home and the financial situation at the age of 10. These factors provide insights into the economic circumstances of the household during early life. To capture long-term potential outcomes, we examine variables such as the number of books available in the household and the relative ability in mathematics and language at the age of 10. These indicators help us understand the potential educational and cognitive advantages or disadvantages individuals may have experienced during childhood. Furthermore, we incorporate a comprehensive set of childhood health conditions to control for the "permanent" or "initial endowment" of health, which can influence both job selection and the long-term trajectory of health outcomes. By considering these multifaceted childhood circumstances, we can account for heterogeneity between different social classes, including factors such as selection into specific jobs, individual preferences for future consequences, time preferences in general, medical investments, harmful habits, and dietary habits.

Further, in order to address unobserved heterogeneity that may have influenced lifetime "success" and response types based on social class, we include current socioeconomic status as a control variable. This control variable takes into account information on household income and educational attainment. Notably, Fletcher et al. (2011) suggests according to the theory of compensating wage differentials (Rosen (1986)), some individuals might accept more harmful jobs that are better remunerated and use these extra earnings to offset the health drops. When these extra investments are neglected, the estimates underestimate the complete effects of occupational stressors. Moreover, Fletcher et al. (2011) point out that income can partially mitigate the impact of occupational stressors on health. Hence, we consider also household income and educational attainment, which can better account for the potential influence of socioeconomic status on the relationship between occupational stressors and health outcomes.

Again, to ensure a comprehensive analysis, several socio-demographic variables are controlled for in the study. These variables include gender, retirement status , age at the time of the interview, country of residence, year of birth, and marital status.

To account for the cumulative impact of work experience, we incorporate data on the total number of years worked in the individual's career up to the time of the interview. This variable helps capture the accumulated exposure to various work-related factors over time. Additionally, for the main job, we control for several factors including whether the job was part-time, whether the individual was a civil servant, employed in a private company, or self-employed. These distinctions help capture the different employment arrangements individuals may have had and their potential influence on the variables under investigation. Furthermore, we include industry fixed effects using the NACE code to control for the specific industry in which individuals are employed. Moreover, it is crucial to control for the number of job changes individuals have made during their careers. This measure captures important unobserved heterogeneity and helps account for any potential confounding factors related to job mobility and its impact on the outcomes of interest.

Finally, in a robustness section, we include controls for various healthy habits. These habits encompass ever smoking daily, leisure time physical inactivity, and the frequency of consuming dairy, legumes/eggs, meat, and fruit. Accounting for individuals who smoked daily allows us to control for differences in harmful health behaviours. Similarly, examining eating and leisure time physical habits serves as proxies to identify individuals who are more likely to engage in protective health behaviours. Moreover, to capture different attitudes and opportunities for investing in health-protecting behaviours throughout one's lifetime, we consider two dimensions: "times talked to a medical doctor/nurse about your health" and "seen a dentist/dental hygienist" within the last 12 months. These measures control for behaviours specifically at the time of the interview. Although they do not provide a complete lifetime picture, they serve as reasonable proxies for long-term habits. Furthermore, to the best of my knowledge, similar information has not been utilized in previous literature. By incorporating these control variables, we aim to account for healthy habits and behaviours that may impact the outcomes under investigation. While there are limitations to the measures in terms of representing only interview time habits, they are expected to provide valuable insights into lifetime habits and offer a novel contribution to the existing literature.

The extensive set of controls included in the analysis addresses potential unobserved heterogeneity that may affect the relationship between occupational stressors and health outcomes. These controls account for various socio-demographic factors, childhood conditions, current socioeconomic status, cumulative work experience, job characteristics, industry fixed effects, and healthy habits. By incorporating these controls, we aim to minimize confounding effects and provide a more accurate assessment of the impact of occupational stressors on health. Moreover, the long retrospective nature of the data allows us to investigate whether individuals self-select into occupations based on their inherited socioeconomic and health characteristics during their youth.

3.2 Descriptive statistics: MET

Here we show the descriptive statistics related to the MET. MET is computed as the weighted average of the Metabolic Equivalent of the Task considering the years spent in each job spell.

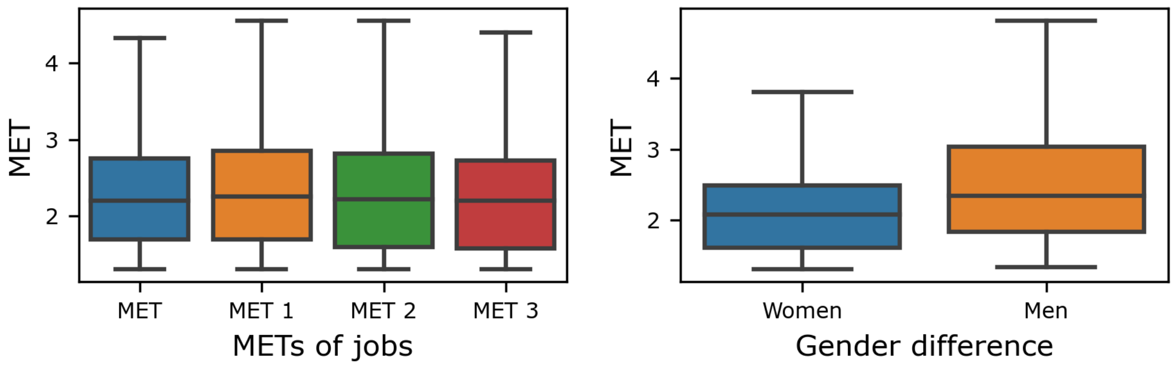


Figure 1: LEFT: Weighted average of the metabolic consumption and the first 3 job episodes. RIGHT: Weighted average of metabolic consumption by gender.

Figure 1 illustrates a gradual decrease in MET values when individuals change jobs. Overall, the gradual decrease in MET values observed in figure 1 can be attributed to a combination of factors, including job transitions towards better positions with lower physical demands and the influence of age-related health limitations prompting individuals to seek less physically demanding occupations. Next, figure 1 shows that men are more exposed to more physically involved jobs.

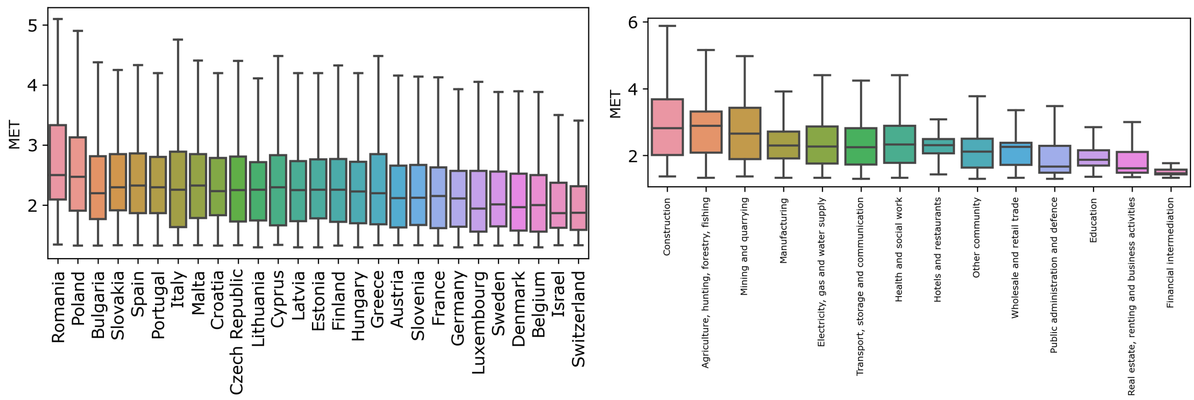


Figure 2: MET by country and MET of the first job by industry of the first job.

Figure 2 highlight that the block of Eastern countries experienced on average more physically involved jobs. Moreover, the "Construction", "Agriculture", and "Mining" sectors are the ones with larger METs. On the opposite, "Financial intermediation" is by far the less physically involved.

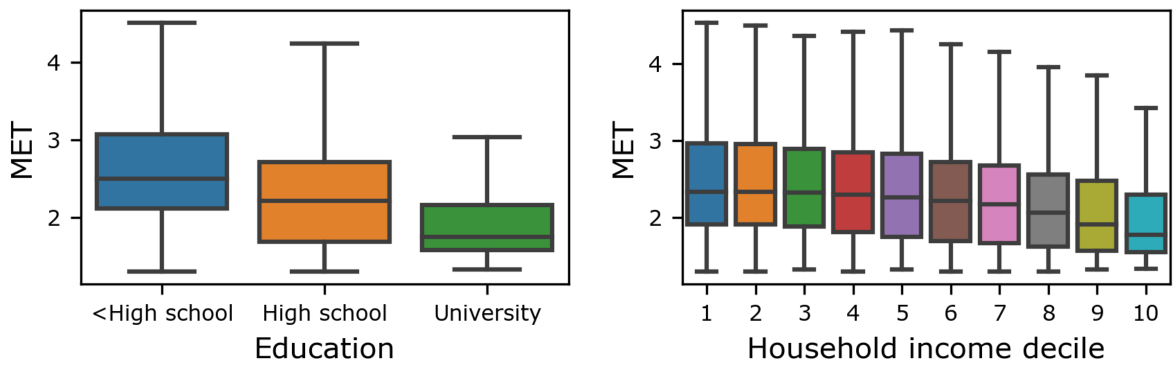


Figure 3: MET by education (ISCED). MET by (current) household income by decile. MET by main breadwinner's MET by decile.

Figure 3 shows a clear educational gradient: education helps to achieve a less physically involved job. Similarly, current household income is negatively related to lower MET.

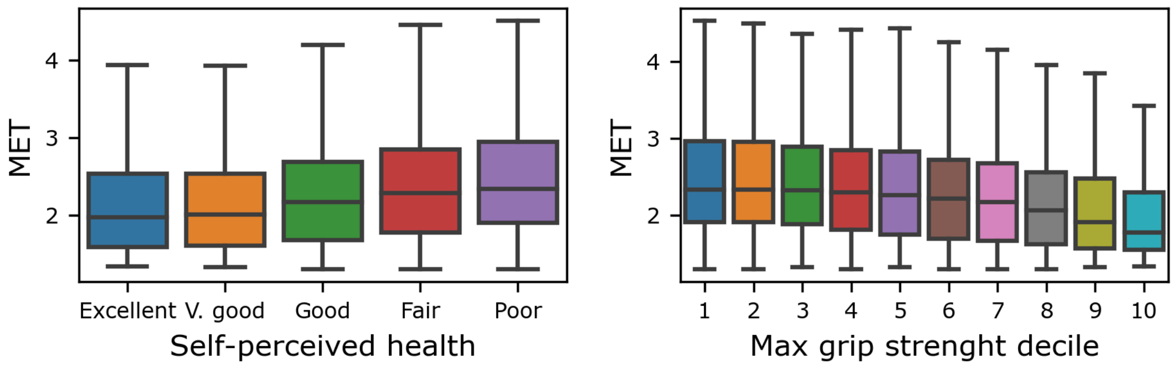


Figure 4: MET by Self-perceived health and Max grip strength.

The descriptive statistics in figure 4 show that working in a more physically involved job is related to both worse self-declared health and objectively measured grip strength.

3.3 Identification issue

The major concern in claiming causality of on-the-job physical energy expenditure and health regards the selection of individuals who are unhealthy or have unhealthy habits into occupations with undesirable characteristics. Again, if individuals with different habits and behaviours also have varying likelihoods of retaining good jobs, reverse causality may introduce bias.

One way to deal with the identification of a causal effect in the literature involves a fixed effects model based on within-individual deviations of occupational stressors and health from their observed averages (Fletcher et al. (2011); Ravesteijn et al. (2018)). However, this approach risks being misleading. In detail, table 5 shows the number of jobs individuals held throughout their careers. Table 5-(a) indicates that over 75% of individuals had fewer than three job spells in their entire career. Turning to table 5-(b), which focuses on the number of different 4-digit ISCO job positions, it becomes evident that nearly 90% of the sample experienced fewer than three types of occupations. Furthermore, Table 5-(c) reveals that more than 43% of the individuals consistently worked in the same 1-digit ISCO code major category. Moreover, as table 6-(a) displays, the vast majority of job changes are made during early adulthood. As a matter of fact, only 15% of total changes are made after 40 years of age, and 3% after the fifties. In contrast, table 6-(b) shows that most individuals (73%) report their first disease after age 50 or do not report any disease at all. In summary, both the diversity of job positions and the variety of job tasks and features experienced by individuals were relatively limited, indicating low job mobility. Moreover, mobility barely happens during older ages, whereas, health is remarkably affected only later in life and is a result of life cumulated events.

To conclude, a fixed-effect model is able to control for fixed unobserved heterogeneity but completely overlooks the time-varying components that are crucial when the entire lifetime is considered. This is particularly concerning as the results do not differentiate between self-selection into occupations and time-varying changes, such as on-the-job network effects or habit adaptation to stressful tasks or working hours. Again, the previous literature used panels with few time observations leading to the risk of capturing only deviations from the mean of health. Moreover, it is not clear how the cumulative strain can be considered. Finally, it does not account for the huge variability in working conditions between individuals.

(a)

N jobs	Freq	%	Cum %
1	11773	29.8	29.8
2	10640	26.9	56.7
3	7088	17.9	74.6
4	4412	11.2	85.8
5 or more	5616	14.2	100
Total	39529	100	

(b)

N jobs (4-digit ISCO)	Freq	%	Cum %
1	14476	36.6	36.6
2	13101	33.1	69.8
3	6803	17.2	87.0
4	3012	7.6	94.6
5 or more	2137	5.4	100
Total	39529	100.0	

(c)

N jobs (1-digit ISCO)	Freq	%	Cum %
1	17105	43.3	43.3
2	14142	35.8	79.0
3	5979	15.1	94.2
4	1795	4.5	98.7
5 or more	508	1.3	100
Total	39529	100.0	

Table 5: (a): Total number of jobs experienced over the entire career. (b): Total number of unique 4-digit ISCO jobs experienced over the entire career. (c): Total number of unique 1-digit ISCO jobs experienced over the entire career.

(a)

Age	Job changes	%	Cum %
10-20	3155	17.4	17.4
21-30	7931	43.8	61.2
31-40	4278	23.6	84.8
41-50	2178	12.0	96.8
51-60	555	3.1	99.9
61-70	23	0.1	100
	18120	100	

(b)

Age	First disease	%	Cum %
10-20	1888	4.8	4.8
21-30	1430	3.6	8.4
31-40	2171	5.5	13.9
41-50	5163	13.1	27.0
51-60	8641	21.9	48.8
61-70	5984	15.1	64.0
No disease	14252	36.0	100
	39529	100	

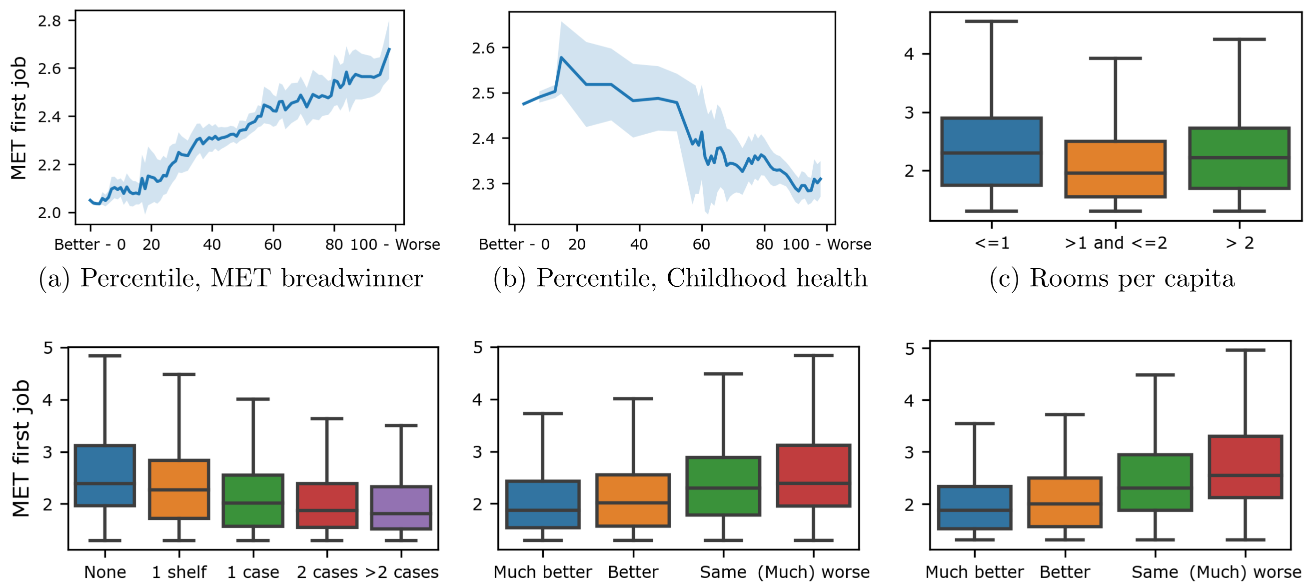
Table 6: (a): Total number of jobs changes by age groups. (b): First disease by age group.

The vast amount of information provided by SHARE allows us to deeply investigate the initial and subsequent selection into specific jobs. Figure 5 shows that selection into the first job[5] is highly related to socioeconomic status during childhood. The intergenerational transmission of job stressors is clear from figure 5a. On average, children with parents experiencing larger energy expenditure in the jobs (METs) are also more likely to work in more physically demanding jobs. Next, figure 5b shows that the "starting" health condition during childhood "selects" individuals with worse health into jobs which

[5]The same identical insights are retrieved if the weighted average of MET consumption of the entire career.

are less physically demanding. Finally, figures 5d, 5e, and 5f show that childhood ability, proxied by books and relative position in maths and language, are important determinants of physical expenditures on the first job. In particular, a higher number of books and greater ability are associated with a reduced level of MET experienced in the initial job.

Controlling for early childhood conditions is important for causal interpretation since they are likely to be related not only to "selection" into jobs but also to other characteristics (e.g. healthy habits) which are directly related to the dynamics of health. Being able to control for them clearly mitigates the omission of important information in determining both the selection into jobs and lifetime behaviour.



(a) Percentile, MET breadwinner (b) Percentile, Childhood health (c) Rooms per capita

(d) Childhood books (e) Childhood math ability (f) Childhood language ability

Figure 5: Childhood conditions and socioeconomic status. EWM span 10

Another important point here is that these conditions are rather exogenous to individuals' decisions. Moreover, since people change a few kinds of jobs in their whole career, the first placement is important in determining lifetime occupational stressors.

Furthermore, reverse causality might be at play. This can occur through two possible channels. Firstly, individuals with poorer health might face challenges in retaining good jobs, leading to transitions into worse-off jobs. Secondly, declining health may limit the pool of available jobs requiring a minimum health threshold, prompting individuals to move toward less demanding occupations. Table 7 reveals that the data does not support the first hypothesis, while providing only limited evidence for the second hypothesis. Specifically, the results of two t-tests investigating the significance of mean differences indicate that individuals with initial worse health have lower METs for both first and last jobs. However, the difference tends to slightly increase in the last job, suggesting a tendency for individuals with worse health to transition toward less physically demanding occupations.

	Better Childhood Health		Worse Childhood Health		
	Mean	Std error	Mean	Std error	ttest
MET first job	2.406	0.005	2.314	0.009	8.517***
MET last job	2.345	0.005	2.243	0.008	10.152***

Table 7: Ttest for the difference in means of the METs in the first and last job according to initial Childhood Health conditions. Better Childhood Health contains 0-74 percentiles, whereas Worse Childhood Health the remaining 75-100 percentiles.

3.4 Regressions

We posit the standard linear model and estimate if through OLS

$$y_i = \beta_0 + \boldsymbol{\beta_1}\mathbf{S}_i + \boldsymbol{\beta}_2\mathbf{X}_i + u_i, \tag{1}$$

where y_i is the health outcome and u_i is the error term. $\boldsymbol{\beta_1}$ is the vector of the effects on the health of increasing the job-specific stressors ($\mathbf{S}_i$) and contains the main parameters of interest. $\mathbf{X}_i$ contains the large set of controls containing the childhood conditions, current socioeconomic conditions, socio-demographic conditions, job details, healthy habits, and medical investment habits. To account for the lifetime aspect of the analysis, the occupational stressors are a weighted mean by considering the years worked in each occupation. To account for the serial correlation in the error term, standard errors are clustered at the 4-digit ISCO code (unit groups), i,e, the level of variation in occupational stressors. We use the SHARELIFE wave 7 sample weights to account for the survey design.

3.5 Results

The main results are reported in table 8.

First, the estimated effect of lifetime physical expenditure (MET)[6] has a particularly large detrimental effect on old age health (this effect is equivalent to ageing more than 6 additional years)[7] if no other controls are used. Similarly, exposure to carcinogenic agents

[6]The increase of MET by one unit is (almost) equivalent of switching from the effort of ”Dental assistants and therapists” (MET = 2) to a ”Hand packers” (MET = 3.10).

[7]As Ravesteijn et al. (2018), to get the effect of age on health, we run a linear regression of Self-perceived poor health on age. An additional year increases the Self-perceived poor health outcome (negative impact) by 0.0266 years.

and working in routine manual jobs deteriorate older ages' health being equivalent to ageing by 0.48 and 10.30 years respectively. On the opposite, more on-the-job psychosocial stress results in increased health as being younger by 0.41 years. Nevertheless, once we control for the other important confounding factors for selection into occupations, only the physical expenditure (MET) remains statistically significant. The baseline result in column (5)[8] of table 9 is roughly one-third of the initial estimate. The baseline effect (table 8 column (5)) of 0.065 can be interpreted as an effect of ageing 2.33 additional years.[9]

To further gain insights about the importance of the confounding variables in explaining the variation in health outcome, in figure 6 we present the Shapley and Owen values (Huettner and Sunder (2012) Roth (1988) Owen (1977)). Shapley and Owen's values are two methods commonly used in cooperative game theory to allocate the contribution of any given player within a cooperative game. Specifically, they consider all possible coalitions and calculate the marginal contribution of each player to each coalition. In the context of an OLS regression, coalitions can be thought of as combinations or subsets of predictor variables that work together to explain the variation in the dependent variable. As expected, the country and the age are explaining the vast majority of the variation in health. It is further interesting to point out that also household income is able to explain more than 10% of the variance in health. Again, within the occupational stressors, MET is explaining slightly more than 2%, in contrast to the other measures which approach zero.

[8] Columns (6) in table 9 provides the same results, but it throws away too many observations to be considered as the main.

[9] To rule out the fact that results are driven by the way job stressors are coded, in the appendix (section 6) we harmonize them to deciles. Results remain robust.

	(1) sphus	(2) sphus	(3) sphus	(4) sphus	(5) sphus	(6) sphus
MET	0.140***	0.140***	0.098***	0.071***	0.066***	0.062***
	(0.023)	(0.020)	(0.019)	(0.017)	(0.017)	(0.020)
Psychosocial stress	-0.011**	-0.006	-0.007	-0.004	-0.004	-0.010
	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)	(0.006)
Carcinogenic agents' exposure	0.013**	0.016***	0.013***	0.009**	0.007	0.007
	(0.006)	(0.004)	(0.004)	(0.004)	(0.005)	(0.006)
Routine manual	0.274***	0.145**	0.058	-0.007	-0.008	0.063
	(0.072)	(0.061)	(0.059)	(0.056)	(0.061)	(0.074)
Routine cognitive	0.047	0.062	0.032	0.009	-0.006	-0.078
	(0.054)	(0.053)	(0.048)	(0.045)	(0.048)	(0.051)
Constant	2.830***	-1.841	0.020	1.029	0.748	3.432***
	(0.061)	(2.795)	(2.504)	(2.522)	(2.590)	(0.370)
Socio-demo		✓	✓	✓	✓	✓
Child			✓	✓	✓	✓
Socio-econ				✓	✓	✓
Job					✓	✓
Habits						✓
Observations	36,946	36,946	29,988	29,988	29,917	20,325
R-squared	0.019	0.113	0.143	0.159	0.176	0.241

Table 8: OLS regressions of Self-perceived poor health outcome on job stressors. Standard errors clustered at the 4-digit ISCO code level of the main job. Used SHARELIFE wave 7 sample weights.

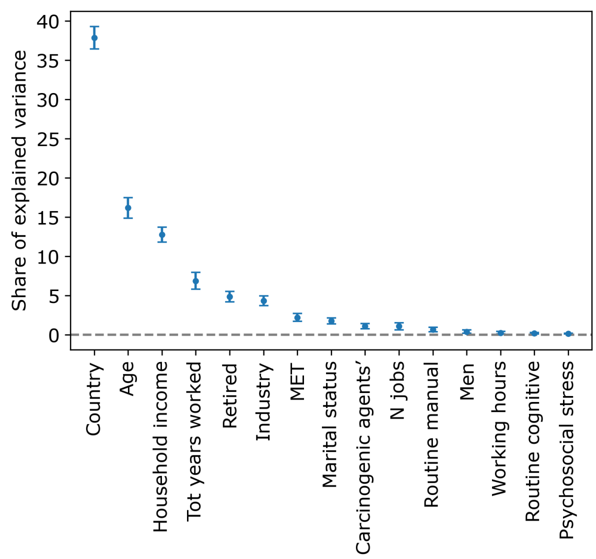


Figure 6: Shares of explained variance (R^2) of the OLS model by each regressor variable computed by Shapley and Owen values.

3.6 Gender

To account for differences in career development, reporting styles, and health dynamics, the results for MET[10] are presented also by gender (table 9). The effects are clearly heterogeneous. Women are suffering much more if compared to men. Men have no significant effect once sociodemographic, childhood, socioeconomic, and job characteristics are taken into account. On the opposite, women experiencing health decrease equivalent to ageing 4.63 additional years.

Gender heterogeneity deserves further discussion and investigation. One possible explanation for the observed gradient may be related to the different biological gender characteristics. As a matter of fact, previous literature shows that the effect of physical work is more detrimental to more physically fragile individuals (Holtermann et al. (2010)). Specifically, the effect of more physically involving tasks performed by women may have a more detrimental effect on their health. However, an alternative explanation involves selection into different jobs, i.e., women perform physically involved tasks which have different features with respect to men ones. This alternative hypothesis is tested in section 5.

	(1) sphus	(2) sphus	(3) sphus	(4) sphus	(5) sphus	(6) sphus
MET - All	0.161*** (0.019)	0.159*** (0.016)	0.109*** (0.016)	0.079*** (0.015)	0.065*** (0.016)	0.062*** (0.020)
MET - Women	0.221*** (0.027)	0.196*** (0.020)	0.119*** (0.019)	0.092*** (0.019)	0.106*** (0.025)	0.111*** (0.035)
MET - Men	0.149*** (0.022)	0.137*** (0.019)	0.108*** (0.021)	0.072*** (0.020)	0.030 (0.021)	0.016 (0.025)
Socio-demo		✓	✓	✓	✓	✓
Childhood			✓	✓	✓	✓
Socio-econ				✓	✓	✓
Job					✓	✓
Habits						✓
Observations - All	36,946	36,946	29,988	29,988	29,917	20,325
R-squared - All	0.015	0.111	0.142	0.159	0.175	0.240

Table 9: OLS estimated of the effect of MET on Self-perceived poor health outcome. Standard errors clustered at the 4-digit ISCO code level of the main job. Used share life wave 7 sample weights.

[10] The other job stressors are included in the "Job" controls since they do not present any statistically significant effect.

4 Robustness of main results

4.1 Oster-test for Omitted Variable Bias

We control the robustness of the results to endogenous self-selection into occupations by means of the Oster-coefficient-stability-test (Oster (2019). The underlying idea of the test is to uncover the omitted variable bias by using the change in coefficients and in R-squared before and after controlling for observed confounding factors. This test is specifically designed for cases in which the link between treatment and unobservables can be fully recovered from the relationship between treatment and observable confounding variables (Altonji et al. (2005)). This approach perfectly suits our context owing to the large set of controlling variables able to control for all the possible selection issues. The primary objective is to compute a value δ such that the treatment effect $\beta = 0$, where δ represents the extent of selection on unobservable factors relative to observable factors required to completely eliminate the treatment effect. A value of $\delta = 1$ would indicate that the unobservable variables would need to be as influential as the observed controls to entirely nullify the estimated treatment effect β.

To identify a value for δ, we have to set the hypothetical maximum value the R-squared could reach by controlling for all observed and unobserved components. In social sciences (especially when survey data is used) the R-squared is rarely equal to one owing to measurement error or to idiosyncratic variation in the outcome variable. Following the insights of Oster (2019), we impose the maximum R-squared equal to 1.5 times the R-squared of the regression with the full set of controls.

Sphus	δ	R^2	Max R^2
All	0.535	0.175	0.263
Women	0.73	0.203	0.305
Men	0.220	0.190	0.285

Table 10: Delta Oster bound. The assumed R^2 is equal to 1.5 the R^2 of the regression with full controls.

Table 10 shows the δs when the outcome is Self-perceived poor health outcome. For the whole sample, the importance of the unobserved components should be around half of the observed dimensions. For women, this share is larger than 70%, and owing to the very large set of controls, this value is quite reassuring. Finally, for men's subgroup is just above 20%, but the baseline estimate is already close to 0 and not statistically significant.

4.2 Other health dimensions

Health is a multidimensional phenomenon, and defining which facet is more important is not straightforward. For the baseline estimate, we employed the measure which is mostly used in literature, i.e., Self-perceived poor health. However, the other dimensions could not have been impacted or hit in different directions. The robustness of the main results is shown in table 11 which contains the other available most important standard health outcomes: ADL, IADL, GALI[11], Mobility limitations, objectively measured maximum grip strength, chronic diseases, BMI, ever-had disability injury, and if health problems limits work. Results are almost always statistically significant and mainly driven by women.

VARIABLES	(1) sphus	(2) adl	(3) iadl	(4) gali	(5) mobility	(6) maxgrip	(7) chronic	(8) bmi	(9) Disability injury	(10) Health limits work
MET - All	0.065***	0.001	0.033**	0.026***	0.114***	-0.062	0.047*	0.357***	0.010*	0.034***
	(0.016)	(0.012)	(0.016)	(0.009)	(0.038)	(0.148)	(0.026)	(0.114)	(0.006)	(0.007)
MET - Women	0.106***	-0.009	0.051**	0.038***	0.157***	-0.388**	0.083**	0.502***	0.007	0.020*
	(0.025)	(0.015)	(0.024)	(0.013)	(0.053)	(0.188)	(0.036)	(0.149)	(0.008)	(0.011)
MET - Men	0.030	0.014	0.026	0.015	0.085*	0.0680	0.046	0.294**	0.009	0.042***
	(0.021)	(0.016)	(0.022)	(0.012)	(0.046)	(0.199)	(0.036)	(0.122)	(0.007)	(0.010)
Observations - All	29,917	29,917	29,917	29,917	29,917	27,867	29,917	29,917	29,914	26,569
R-squared - All	0.175	0.055	0.072	0.134	0.162	0.131	0.194	0.075	0.063	0.143

Table 11: OLS regression of other health dimensions on MET. Specification from column (5) in table 9.

Next, it is interesting to investigate the impact of various diseases on health. To achieve this, we analyse information regarding diseases experienced at least once throughout the individuals' lifetimes. Since our sample comprises individuals aged 50 and above who inherently have a higher likelihood of encountering diseases, we initially examine the effect of MET on the age of the first disease. The results are presented in Tables 12 and 13. Notably, exposure to one additional MET is associated with an advancement in the onset of the first disease by approximately 1 year. This effect is predominantly observed in women. Furthermore, consistent with previous studies Holtermann et al. (2010); Krause et al. (2015), men engaged in physically demanding tasks during their occupations are 1.5% more likely to experience a heart attack. Additionally, men are also more prone to developing emotional disorders. In contrast, women who undertake physically demanding tasks in their careers are more likely to experience hypertension and diabetes.

[11] Dummy indicating any limitations with activities.

VARIABLES	Age first disease	Heart attack	Hypertension	Cholesterol	Stroke	Diabetes	Lung	Cancer	Stomach
MET - All	-0.819***	0.012**	0.017	0.003	0.005	0.004	-0.001	0.004	-0.001
	(0.318)	(0.005)	(0.012)	(0.007)	(0.004)	(0.007)	(0.004)	(0.004)	(0.003)
MET - Women	-0.910*	0.006	0.031**	0.001	-0.001	0.038***	0.005	-0.002	-0.004
	(0.502)	(0.007)	(0.013)	(0.010)	(0.004)	(0.008)	(0.005)	(0.006)	(0.004)
MET - Men	-0.434	0.015**	0.015	0.012	0.008	-0.015*	-0.006	0.005	0.001
	(0.466)	(0.008)	(0.016)	(0.011)	(0.006)	(0.009)	(0.006)	(0.005)	(0.005)
Observations	19,880	29,886	29,886	29,892	29,805	29,805	29,805	29,805	29,805
R-squared	0.157	0.175	0.122	0.149	0.076	0.082	0.064	0.040	0.056

Table 12: OLS regression of diseases experienced at least once on MET. Specification from column (5) in table 9.

VARIABLES	Parkinson	Cataracts	Hip fractures	Other fractures	Alzheimer	Emotional disorders	Rheumatoid arthritis	Osteoarthritis	Kidney
MET - All	-0.001	-0.004	-0.004*	0.000	-0.000	0.007	-0.006	0.007	0.001
	(0.001)	(0.004)	(0.002)	(0.004)	(0.002)	(0.005)	(0.004)	(0.006)	(0.002)
MET - Women	0.000	-0.005	-0.004	-0.001	-0.001	0.001	-0.003	0.010	0.003
	(0.001)	(0.005)	(0.004)	(0.005)	(0.002)	(0.007)	(0.007)	(0.012)	(0.005)
MET - Men	-0.000	-0.006	-0.004	0.005	0.002	0.012**	-0.003	0.010	-0.002
	(0.002)	(0.006)	(0.003)	(0.006)	(0.003)	(0.006)	(0.005)	(0.007)	(0.003)
Observations	29,805	29,805	29,805	29,805	29,805	29,805	29,805	29,805	29,805
R-squared	0.018	0.078	0.056	0.039	0.032	0.082	0.077	0.119	0.039

Table 13: OLS regression of diseases experienced at least once on MET. Specification from column (5) in table 9.

4.3 Estimation through Causal Forest

Another possible concern regards functional form misspecification. To control if interaction terms and non-linearities play an important role in the basic linear model, we run a Causal Forest within the Generalized Random Forest algorithm Athey et al. (2019). The Causal Forest allows us to perform a more flexible estimation and in addition, does not throw away missing controls allowing us to keep roughly 20% more observations. Furthermore, the Causal Forest estimates individual treatment effects which can be used to perform a calibration test for the validity of the "treatment effect". Table 14 shows that the main difference between OLS and Causal Forest is that the point estimates of the OLS are smaller. Nevertheless, it is reassuring to note that the economic interpretation of the findings remains consistent, as the overall effects and significance tests are robust across the two estimators.

Next, table 15 presents the estimates and p-values of the calibration tests inspired by the "best linear model" (Chernozhukov et al. (2018)). An estimate close to 1 and statistically different from 0 indicates that the individual treatment effects effectively explain the average treatment effect. Notably, nearly all point estimates of the calibration tests are close to 1 and statistically different from 0, providing compelling evidence in support of the validity of the estimated effects.

Moreover, in this study, we re-estimated the analysis that examines the relationship between MET and diseases, utilising the Causal Forest method. We then compared these results with estimates obtained through OLS regression. The findings indicate a high degree of consistency in relation to the age of the first disease between both approaches. Additionally, the two procedures demonstrate comparable results concerning health attacks and diabetes. However, it is worth noting that certain discrepancies were observed in other aspects of the analysis. Despite these variations, the overall conclusion points to the two methods yielding similar results.

VARIABLES	(1) sphus	(2) adl	(3) iadl	(4) gali	(5) mobility	(6) maxgrip	(7) chronic	(8) bmi	(9) Disability injury	(10) Health limits work
MET - All - OLS	0.065***	0.001	0.033**	0.026***	0.114***	-0.062	0.047*	0.357***	0.010*	0.034***
	(0.016)	(0.012)	(0.016)	(0.009)	(0.038)	(0.148)	(0.026)	(0.114)	(0.006)	(0.007)
MET - All - CF	0.11***	0.021	0.042*	0.052***	0.199***	0.018	0.126***	0.75***	0.008	0.066***
	(0.026)	(0.015)	(0.024)	(0.015)	(0.048)	(0.191)	(0.048)	(0.16)	(0.01)	(0.017)
MET - Women - OLS	0.106***	-0.009	0.051**	0.038***	0.157***	-0.388**	0.083**	0.502***	0.007	0.020*
	(0.025)	(0.015)	(0.024)	(0.013)	(0.053)	(0.188)	(0.036)	(0.149)	(0.008)	(0.011)
MET - Women - CF	0.138***	0.04**	0.097***	0.073***	0.313***	-0.042	0.161**	0.919***	0.001	0.057***
	(0.044)	(0.018)	(0.035)	(0.023)	(0.088)	(0.228)	(0.079)	(0.266)	(0.011)	(0.019)
MET - Men - OLS	0.030	0.014	0.026	0.015	0.085*	0.068	0.046	0.294**	0.009	0.042***
	(0.021)	(0.016)	(0.022)	(0.012)	(0.046)	(0.199)	(0.036)	(0.122)	(0.007)	(0.010)
MET - Men - CF	0.076**	0.012	0.029	0.029*	0.094	0.128	0.086*	0.543***	0.019	0.073***
	(0.033)	(0.021)	(0.029)	(0.017)	(0.059)	(0.267)	(0.045)	(0.172)	(0.012)	(0.015)
Observations - All										

Table 14: OLS regression and Causal Forest estimates of other health dimensions on MET. Specification from column (5) in table 9.

	(1) sphus	(2) adl	(3) iadl	(4) gali	(5) mobility	(6) maxgrip	(7) chronic	(8) bmi	(9) Disability injury	(10) Health limits work
Est	0.946	1.056	1.201	0.81	1.012	-0.131	1.035	0.985	1.072	0.939
p-value	0.001	0.161	0.067	0.01	0.002	0.506	0.006	0.003	0.235	0

Table 15: Calibration test for the validity of the average treatment effect.

VARIABLES	Age First Disease	Heart attack	Hypertension	Cholesterol	Stroke	Diabetes	Lung	Cancer	Stomach
MET - All - OLS	-0.819**	0.012**	0.017	0.003	0.005	0.004	-0.001	0.004	-0.001
	(0.318)	(0.005)	(0.012)	(0.007)	(0.004)	(0.007)	(0.004)	(0.004)	(0.003)
MET - All - CF	-1.29*	0.016*	0.022	0.007	0.007	0.021*	0.017***	-0.001	0.006
	(0.702)	(0.009)	(0.018)	(0.01)	(0.005)	(0.012)	(0.006)	(0.005)	(0.004)
MET - Women - OLS	-0.910*	0.006	0.031**	0.001	-0.001	0.038***	0.005	-0.002	-0.004
	(0.502)	(0.007)	(0.013)	(0.010)	(0.004)	(0.008)	(0.005)	(0.006)	(0.004)
MET - Women - CF	-1.744*	0.014	0.023	0.021	-0.002	0.044***	0.023**	0.001	0.009
	(1.061)	(0.014)	(0.019)	(0.015)	(0.004)	(0.013)	(0.009)	(0.008)	(0.007)
MET - Men - OLS	-0.434	0.015**	0.015	0.012	0.008	-0.015*	-0.006	0.005	0.001
	(0.466)	(0.008)	(0.016)	(0.011)	(0.006)	(0.009)	(0.006)	(0.005)	(0.005)
MET - Men - CF	-0.802	0.016*	0.026	0.006	0.012*	-0.005	0.011*	-0.002	0.004
	(0.752)	(0.009)	(0.022)	(0.014)	(0.007)	(0.011)	(0.006)	(0.008)	(0.006)
R-squared	0.175	0.122	0.149	0.076	0.082	0.064	0.040	0.056	
Observations CF	39,362	39,362	39,362	39,362	39,362	39,362	39,362	39,362	

Table 16: OLS regression and Causal Forest estimates of diseases experienced at least once on MET. Specification from column (5) in table 9.

VARIABLES	Parkinson	Cataracts	Hip fractures	Other fractures	Alzheimer	Emotional disorders	Rheumatoid arthritis	Osteoarthritis	Kidney
MET - All - OLS	-0.001	-0.004	-0.004*	0.000	-0.000	0.007	-0.006	0.007	0.001
	(0.001)	(0.004)	(0.002)	(0.004)	(0.002)	(0.005)	(0.004)	(0.006)	(0.002)
MET - All - CF	-0.003***	0	-0.005*	0.003	0	0.005	0.011	0.014	0.002
	(0.001)	(0.006)	(0.003)	(0.006)	(0.002)	(0.008)	(0.008)	(0.015)	(0.004)
MET - Women - OLS	0.000	-0.005	-0.004	-0.001	-0.001	0.001	-0.003	0.010	0.003
	(0.001)	(0.005)	(0.004)	(0.005)	(0.002)	(0.007)	(0.007)	(0.012)	(0.005)
MET - Women - CF	-0.002	0.002	-0.007	-0.009	0.001	0.01	0.015	0.035	0.007
	(0.002)	(0.011)	(0.005)	(0.007)	(0.002)	(0.015)	(0.015)	(0.024)	(0.006)
MET - Men - OLS	-0.000	-0.006	-0.004	0.005	0.002	0.012**	-0.003	0.010	-0.002
	(0.002)	(0.006)	(0.003)	(0.006)	(0.003)	(0.006)	(0.005)	(0.007)	(0.003)
MET - Men - CF	-0.004**	-0.007	-0.002	0.016*	0.002	0.01	0.008	-0.001	-0.003
	(0.002)	(0.006)	(0.003)	(0.009)	(0.003)	(0.008)	(0.006)	(0.011)	(0.003)
R-squared	0.018	0.078	0.056	0.039	0.032	0.082	0.077	0.119	0.039
Observations CF	39,362	39,362	39,362	39,362	39,362	39,362	39,362	39,362	39,362

Table 17: OLS regression and Causal Forest estimates of diseases experienced at least once on MET. Specification from column (5) in table 9.

5 LASSO to detect the most harmful tasks

In this section, we introduce a novel approach to develop a new "Job Strain Intensity" measure. To achieve this, we leverage the LASSO estimator and granular job-specific tasks at each 4-digit ISCO code.

5.1 LASSO estimator and granular job-specific tasks

The ISCO classification framework allows us also to further investigate the role of each job-specific task on health. As a matter of fact, for each 4-digit ISCO code, ILO[12]

[12] https://www.ilo.org/public/english/bureau/stat/isco/docs/groupdefn08.pdf

provides a list of job-specific tasks. However, the tasks are not directly comparable with each other. To do so, we use the categorisation proposed by Deyaert et al. (2017) which assigned each job-specific task to a more homogenised task. For instance, the tasks of "serving on government administrative boards or official committees" (1111 - Legislators), "participating in departmental and faculty meetings and in conferences and seminars" (2310 - University and higher education teacher), and "advising clients on legal matters" (3411 - Legal and related associate professionals) are aggregated in the same homogenised task "Meetings". Overall, they propose 352 homogenised tasks.

To understand which job-specific tasks are affecting more old-age Self-perceived poor health, we rely on the LASSO estimation (Tibshirani (1996)):

$$\min_{\gamma}\left(\frac{1}{N}\sum_{i=1}^{N}(y_i-\beta_0-\sum_{k=1}^{q}z_{ik}\gamma_k)^2+\lambda\sum_{j=1}^{q}|\gamma_j|\right) \tag{2}$$

where i denotes the individual, k the task, and q is the total number of homogenised tasks. y_i is the health outcome of individual i. z_{ik} is a dummy assuming value 1 if the individual i performed the task k. λ is the shrinking/regularisation parameter.

The main idea is to regress the Self-perceived poor health outcome of the individuals in our dataset on the 352 dummies of the homogenised tasks performed in the main job. The LASSO estimation perfectly suits our goal since we start from a huge sparse homogenised tasks matrix. To capture the tasks which are more harmful to health, we impose a positive restriction on the sign of the coefficients γ_k. To determine the optimal parameter λ we employ 100 cross-validations. To sum up, this approach detects 99 (out of the 352) tasks that are more harmful to Self-perceived health (table 25 of the appendix shows the selected harmful tasks).

5.2 Job Strain Intensity

To construct the job strain intensity dimension, we utilise the previous 99 tasks to calculate the proportion of harmful tasks within each 4-digit ISCO code. This proportion represents the share of harmful tasks relative to the total tasks associated with a specific 4-digit ISCO occupation[13]. By computing this proportion for each 4-digit ISCO code, we aim to capture the intensity of job strain experienced by individuals by solely relying on a data-driven approach. It is worth highlighting that this measure captures the overall job strain activities including both the observable measures such as MET, but also unobserved job characteristics which are more difficult to spot.

[13]The implicit assumption is that all tasks within a 4-digit ISCO code are performed for equal amounts of time.

Figure 7 displays the distribution of job strain intensities, with nearly 25% of the sample showing no harmful tasks. Within this group of zero job strain intensity, table 18 illustrates that over 90% consists of white-collar occupations. Moving beyond the 0-peak, the distribution in figure 7 takes on a more uniform pattern. Moreover, table 18 reveals that the ISCO codes in the tenth decile, representing the most intense job strains, are dominated by over 85% of blue-collar ISCO codes.

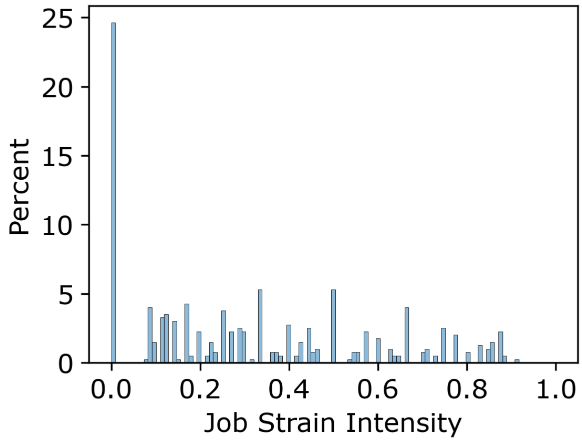


Figure 7: Percent of job strain intensity for the 4-digit ISCO codes.

% of ISCO codes in	Zero Job Strain Intensity group	10^{th} decile group
1-Managers	6	0
2-Professionals	40	2
3-Technicians and professionals	23	4
4-Clerical support workers	13	0
5-Service and sales workers	8	8
6-Skilled agricultural	0	0
7-Craft and related trades workers	4	40
8-Plant and machine operators	2	31
9-Elementary occupations	3	15
Total	100	100

Table 18: Share of ISCO codes conditional of being the in the group of the 4-digit ISCO codes with zero job strain intensity and the tenth decile containing the most affected ISCO codes.

This new measure captures the variability of job strain conditions between 4-digit ISCO codes. To further show the validity of this measure, figure 8 presents the average job strain intensity categorised by 1-digit ISCO codes. As expected, blue-collar workers exhibit higher job strain intensity, aligning with the widely recognised distinction between white-collar and blue-collar work environments.

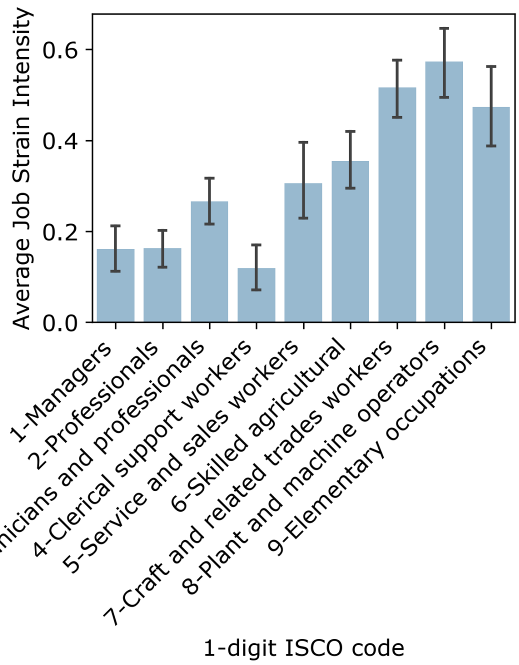


Figure 8: Average job strain intensity by 1-digit ISCO codes.

5.3 Estimation results for Job Strain Intensity

In this section, we adopt the same linear model as described in section 3.4. Now, the focus is on the Job Strain Intensity (JSI) measure and the Metabolic Equivalent of Task (MET). Again, the central aspect of our identification strategy hinges on the comprehensive inclusion of all confounding variables to address potential selection biases.

Table 19 displays the results. Column (1) shows the results of regressing the Self-perceived poor health only on the Job Strain Intensity. The effect size of 0.439 is both statistically significant and substantial, as it corresponds to an ageing effect of approximately 16.5 years[14]. In Column (2), we extend the analysis to include the MET control. The findings indicate that the Job Strain Intensity explains a portion of the variance accounted for by the MET variables. Despite this, the Job Strain Intensity remains statistically significant, although its effect size decreases by approximately one-third when the MET variable is introduced as a predictor. Likewise, the coefficient of the MET variable also experiences a reduction of almost one-third compared to its standalone regression in table 8 - column (1). Subsequently, with the sequential inclusion of the remaining confounding factors, the magnitudes of both coefficients decrease. However, it is noteworthy that throughout this process, the statistical significance of the coefficients consistently remains at the 1% level. Specifically, column (6) reveals that an increase

[14] Let us recall that ageing one additional year corresponds to an effect of 0.0266 on Self-perceived health.

of one unit in the Job Strain Intensity (JSI) variable corresponds to an ageing effect of approximately 4.13 additional years. However, it's important to note that JSI is a continuous variable with a range from 0 to 1, making an increase of 1 unit quite extreme. To provide a more meaningful interpretation, an increase of 1 standard deviation in JSI, which is approximately 0.3, corresponds to an ageing effect of approximately 1.24 additional years. Similarly, the results in column (6) indicate that an increase of one unit in the MET variable corresponds to an ageing effect of approximately 2 additional years. To provide a more interpretable context, if we were to increase the MET variable by 0.78, which corresponds to one standard deviation, the associated ageing effect would be approximately 1.58 additional years.

These results contribute valuable insights to the discussion. On one hand, if the complete set of confounding variables controls for endogenous selection into jobs, the Job Strain Intensity emerges as a novel measure. It effectively captures important job dimensions that influence old-age health, which are otherwise challenging to measure using conventional methods. Furthermore, as highlighted in section 5.4, this approach facilitates a detailed and precise disentanglement of the 4-digit ISCO codes that experience the most significant impact. On the other hand, in the case where the set of confounding variables cannot entirely account for endogenous selection into jobs, the influence of Job Strain Intensity encompasses both adverse job dimensions and unobserved characteristics. Still, this would provide further evidence about the robustness of the results related to MET. Specifically, the MET effect in column (6) is economically equivalent to the main results (table 9) even when accounting for unobserved characteristics measured by Job Strain Intensity.

VARIABLES	(1) sphus	(2) sphus	(3) sphus	(4) sphus	(5) sphus	(6) sphus
Job Strain Intensity	0.439***	0.302***	0.220***	0.191***	0.148***	0.110***
	(0.045)	(0.047)	(0.046)	(0.042)	(0.036)	(0.040)
MET		0.107***	0.119***	0.077***	0.055***	0.054***
		(0.019)	(0.016)	(0.016)	(0.015)	(0.017)
Psychosocial stress						-0.004
						(0.005)
Carcinogenic agents' exposure						0.005
						(0.005)
Routine manual						-0.025
						(0.061)
Routine cognitive						-0.000
						(0.047)
Constant	3.052***	2.851***	-1.786	0.099	1.210	0.899
	(0.022)	(0.042)	(2.788)	(2.493)	(2.506)	(2.583)
MET		✓	✓	✓	✓	✓
Socio-demo			✓	✓	✓	✓
Childhood				✓	✓	✓
Socio-econ					✓	✓
Job						✓
Habits						
Observations	36,898	36,898	36,898	29,956	29,956	29,885
R-squared	0.016	0.021	0.114	0.145	0.160	0.177

Table 19: OLS regressions of Self-perceived poor health outcome on job stressors, including the unobserved job-strain. Standard errors clustered at the 4-digit ISCO code level of the main job. Used SHARELIFE wave 7 sample weights.

5.4 Most harmful tasks and jobs

Our approach allows us to further expand the analysis to a more granular level. Specifically, instead of tuning the penalisation term λ with the aim to minimise the predictive error as in the standard LASSO approach, we impose the penalisation term λ in order to provide the 5 most impacting tasks.

The above-mentioned LASSO procedure detects the following tasks as the most predictive in health deterioration:

- Construction and restoration
- Operating heavy-duty equipment
- Repair/maintenance
- Preparing, cooking, serving meals

- Sweeping, vacuum-cleaning, polishing and washing

Tables 20 and 21 display the 4-digit ISCO code jobs that include at least one of the five most detrimental tasks identified by the LASSO analysis. As expected, the first task "Construction and restoration" contains bricklayers and building construction workers. Next, the "Operating heavy-duty equipment" task contains mostly the jobs from the ISCO major group of "Plant and Machine Operators and Assemblers". Further, the "Repair/maintenance" task includes gardeners, forestry workers, and manufacturing labourers. All these jobs have a prevalence of men's employment. On the contrary, the two remaining tasks are characterised by a large number of women's participation. First, the "Preparing, cooking, serving meals" task embodies cooks, waiters, and kitchen helpers in general. Then, the "Sweeping, vacuum-cleaning, polishing and washing" task includes cleaners in general.

ISCO	ISCO	MET	OSI	CAI	RM	RC	JSI	Share men	Total workers
Task: Construction and restoration									
6113	Gardeners, horticultural and nursery growers	3.15	6.0	8	0.13	0.07	0.46	0.48	104
7111	House builders	3.66	2.0	10	0.00	0.00	0.75	0.93	125
7112	Bricklayers and related workers	4.20	2.0	10	0.00	0.00	0.75	0.96	368
7113	Stonemasons, stone cutters, splitters and carvers	3.63	2.0	10	0.00	0.14	0.38	0.82	33
7114	Concrete placers, concrete finishers and relate...	3.68	3.0	10	0.00	0.00	0.67	0.98	42
7119	Building frame and related trades workers not e...	3.50	3.0	10	0.00	0.00	0.75	0.93	42
7121	Roofers	4.05	3.0	10	0.00	0.00	0.71	0.94	18
7123	Plasterers	3.32	2.0	10	0.00	0.00	0.20	0.83	24
7124	Insulation workers	2.77	2.0	10	0.17	0.00	0.71	0.70	23
7214	Structural metal preparers and erectors	3.33	3.0	10	0.50	0.00	0.71	0.89	82
9313	Building construction labourers	4.90	7.0	10	0.00	0.00	0.57	0.80	205
Task: Operating heavy-duty equipment									
7113	Stonemasons, stone cutters, splitters and carvers	3.63	2.0	10	0.00	0.14	0.38	0.82	33
7119	Building frame and related trades workers not e...	3.50	3.0	10	0.00	0.00	0.75	0.93	42
7221	Blacksmiths, hammersmiths and forging press wor...	3.42	7.0	10	0.62	0.25	0.44	0.79	58
7223	Metal working machine tool setters and operators	2.55	8.0	9	0.67	0.17	0.71	0.83	131
8122	Metal finishing, plating and coating machine op...	2.48	10.0	10	0.88	0.12	0.11	0.76	46
8141	Rubber products machine operators	2.33	10.0	10	0.67	0.17	0.57	0.50	10
8142	Plastic products machine operators	2.33	8.0	10	0.75	0.12	0.62	0.40	42
8143	Paper products machine operators	2.50	10.0	10	1.00	0.00	0.75	0.56	27
8151	Fibre preparing, spinning and winding machine o...	2.55	10.0	10	1.00	0.00	0.85	0.13	46
8152	Weaving and knitting machine operators	2.54	10.0	10	0.85	0.00	0.86	0.05	41
8153	Sewing machine operators	2.44	9.0	9	0.88	0.00	0.78	0.00	77
8154	Bleaching, dyeing and fabric cleaning machine o...	2.52	8.0	10	0.92	0.00	0.85	0.28	18
8157	Laundry machine operators	2.90	9.0	9	0.56	0.00	0.50	0.00	11
8160	Food and related products machine operators	2.50	10.0	9	1.00	0.00	0.88	0.39	93
8171	Pulp and papermaking plant operators	2.22	10.0	10	0.50	0.20	0.67	0.64	11
8172	Wood processing plant operators	3.50	9.0	10	0.80	0.00	0.67	0.75	40
8181	Glass and ceramics plant operators	2.46	10.0	10	0.92	0.08	0.86	0.58	12
8182	Steam engine and boiler operators	2.06	10.0	10	0.40	0.30	0.88	0.86	28
8183	Packing, bottling and labelling machine operators	2.50	10.0	10	1.00	0.00	0.75	0.23	26
8212	Electrical and electronic equipment assemblers	2.06	8.0	8	0.40	0.60	0.50	0.57	75
8341	Mobile farm and forestry plant operators	2.89	7.0	9	0.00	0.00	0.67	0.94	64
8342	Earthmoving and related plant operators	2.50	4.0	10	0.00	0.00	0.88	0.96	70
8343	Crane, hoist and related plant operators	2.33	8.0	9	0.00	0.00	0.88	0.68	74
Task: Repair/maintenance									
6113	Gardeners, horticultural and nursery growers	3.15	6.0	8	0.13	0.07	0.46	0.48	104
6121	Livestock and dairy producers	3.03	7.0	9	0.13	0.07	0.64	0.27	124
6130	Mixed crop and animal producers	3.15	7.0	9	0.07	0.07	0.27	0.73	44
9215	Forestry labourers	5.14	3.0	9	0.00	0.00	0.22	0.80	10
9329	Manufacturing labourers not elsewhere classified	4.25	9.0	9	0.60	0.00	0.80	0.39	228

Table 20: Jobs related to the tasks detected by the LASSO procedure. Part 1.

ISCO	ISCO08Label	MET	OSI	CAI	RM	RC	JSI	Share men	Total workers
Task: Preparing, cooking, serving meals									
3434	Chefs	2.61	8.0	9	0.00	0.25	0.27	0.38	45
5111	Travel attendants and travel stewards	2.07	10.0	8	0.00	0.25	0.25	0.32	25
5120	Cooks	2.33	7.0	8	0.11	0.22	0.62	0.18	391
5131	Waiters	2.14	10.0	7	0.00	0.14	0.25	0.28	257
5132	Bartenders	2.26	9.0	9	0.09	0.18	0.36	0.47	43
5152	Domestic housekeepers	2.53	7.0	8	0.00	0.27	0.70	0.08	38
5212	Street food salespersons	2.70	6.0	4	0.00	0.17	0.33	0.22	23
5246	Food service counter attendants	2.14	9.0	7	0.00	0.20	0.78	0.03	29
7511	Butchers, fishmongers and related food preparers	2.81	10.0	6	0.56	0.11	0.78	0.65	117
7513	Dairy products makers	2.29	10.0	8	0.75	0.25	0.67	0.70	10
9111	Domestic cleaners and helpers	2.39	7.0	7	0.00	0.00	0.50	0.00	282
9411	Fast food preparers	2.40	10.0	8	0.00	0.22	0.60	0.29	14
9412	Kitchen helpers	3.01	9.0	8	0.00	0.00	0.88	0.03	157
Task: Sweeping, vacuum-cleaning, polishing and washing									
5151	Cleaning and housekeeping supervisors in office...	2.39	6.0	8	0.0	0.22	0.78	0.18	44
5152	Domestic housekeepers	2.53	7.0	8	0.0	0.27	0.70	0.08	38
9111	Domestic cleaners and helpers	2.39	7.0	7	0.0	0.00	0.50	0.00	282
9112	Cleaners and helpers in offices, hotels and oth...	2.85	9.0	7	0.0	0.00	0.80	0.04	416
9613	Sweepers and related labourers	3.68	4.0	7	0.0	0.00	0.80	0.35	26

Table 21: Jobs related to the five most harmful tasks detected by the LASSO procedure. Part 2.

An intriguing aspect to consider is the additional information offered by the Job Strain Intensity measure. While the routine measures proposed by Mihaylov and Tijdens (2019) focus solely on tasks that are potentially replaceable by robots (likely to capture the "Plant and Machine Operators and Assemblers" tasks) they may not encompass other forms of general routineness. For example, routine jobs that cannot be replaced by robots but involve ergonomic stress due to repetitive tasks, like "Sweeping, vacuum-cleaning, polishing, and washing," are not classified as Routine Manual tasks. Nevertheless, the Job Strain Intensity exhibits notably high values in such cases. This highlights the Job Strain Intensity as a promising candidate for addressing this and other unobserved and challenging-to-measure job characteristics.

It is crucial to emphasize that the current approach does not directly consider self-selection into occupations. Nevertheless, the results remain robust even after introducing baseline controls to account for self-selection into jobs. Specifically, the procedure involves sequentially updating the shrinking parameter λ until five tasks are selected, yielding the identification of the five most harmful tasks, which are as follows: "Preparing, cooking, and serving meals"; "Repair/maintenance"; "Sweeping, vacuum-cleaning, polishing and washing"; "Stock control"; "Unloading trucks".

The availability of the JSI measure at the 4-digit ISCO code level enhances the depth of analysis. As highlighted in Table 18, a significant majority of job tasks belong to the blue-collar category. In Table 22, we delve deeper by presenting the ISCO codes belonging to the worst decile, specifically those with JSI values exceeding 0.75. Interestingly, we find that several occupations listed in tables 20 and 21 are also reported here. Among the 42 occupations presented here, 21 are also identified in the previous section, which relied solely on at least one task performed out of the five most harmful tasks. This new list represents a further refinement as it considers not just one harmful task but the mixture of all tasks, resulting in a more comprehensive representation of the job hazards.

In this subsection, we explicitly identify tasks and occupations that are linked to poor Self-perceived health in older ages. The usefulness of this approach for policy-makers is evident in at least two scenarios. First, when implementing interventions concerning statutory retirement ages, a generalised increase may negatively impact the equality of the pension system in terms of both life expectancy and healthy life expectancy. However, by identifying specific job positions that are more likely to impact health during older ages, targeted retirement terms can be designed to address these concerns more effectively. Secondly, identifying tasks and job positions that are more prone to health risks enables policymakers to concentrate on formulating targeted safety regulations at work. Additionally, pinpointing the most hazardous tasks can guide investments towards automation or optimisation, aiming to mitigate the detrimental impact on health and improve overall workplace safety.

ISCO	ISCO08Label	MET	OSI	CAI	RM	RC	JSI	Share men	Total workers
2655	Actors	1.90	8.0	2	0.00	0.00	0.88	0.53	34
3111	Chemical and physical science technicians	1.76	2.0	8	0.00	0.60	0.75	0.70	10
3521	Broadcasting and audio-visual technicians	2.07	8.0	6	0.00	0.57	0.88	0.76	42
5151	Cleaning and housekeeping supervisors in office...	2.39	6.0	8	0.00	0.22	0.78	0.18	44
5223	Shop sales assistants	2.30	5.0	4	0.00	0.33	0.83	0.14	804
5230	Cashiers and ticket clerks	1.58	10.0	5	0.00	0.88	0.89	0.05	77
5246	Food service counter attendants	2.14	9.0	7	0.00	0.20	0.78	0.03	29
7111	House builders	3.66	2.0	10	0.00	0.00	0.75	0.93	125
7112	Bricklayers and related workers	4.20	2.0	10	0.00	0.00	0.75	0.96	368
7119	Building frame and related trades workers not e...	3.50	3.0	10	0.00	0.00	0.75	0.93	42
7133	Building structure cleaners	4.83	3.0	10	0.00	0.00	0.75	0.54	35
7211	Metal moulders and coremakers	2.64	7.0	10	0.86	0.00	0.88	0.79	24
7212	Welders and flame cutters	2.72	7.0	10	0.75	0.12	0.78	0.95	161
7231	Motor vehicle mechanics and repairers	3.11	8.0	9	0.00	0.00	0.89	0.95	278
7311	Precision-instrument makers and repairers	1.94	3.0	8	0.08	0.33	0.85	0.81	37
7313	Jewellery and precious metal workers	1.84	4.0	8	0.00	0.09	0.83	0.57	14
7411	Building and related electricians	2.69	4.0	9	0.00	0.12	0.78	0.93	169
7412	Electrical mechanics and fitters	3.30	5.0	9	0.00	0.22	0.88	0.91	189
7422	Information and communications technology insta...	2.81	3.0	6	0.00	0.33	0.75	0.87	45
7511	Butchers, fishmongers and related food preparers	2.81	10.0	6	0.56	0.11	0.78	0.65	117
7522	Cabinet-makers and related workers	2.63	3.0	10	0.38	0.12	0.86	0.73	83
7523	Woodworking machine tool setters and operators	1.92	8.0	10	0.43	0.14	0.86	0.63	52
7533	Sewing, embroidery and related workers	1.91	5.0	10	0.08	0.00	0.85	0.01	277
8132	Photographic products machine operators	1.88	9.0	9	0.78	0.11	0.78	0.20	5
8143	Paper products machine operators	2.50	10.0	10	1.00	0.00	0.75	0.56	27
8151	Fibre preparing, spinning and winding machine o...	2.55	10.0	10	1.00	0.00	0.85	0.13	46
8152	Weaving and knitting machine operators	2.54	10.0	10	0.85	0.00	0.86	0.05	41
8153	Sewing machine operators	2.44	9.0	9	0.88	0.00	0.78	0.00	77
8154	Bleaching, dyeing and fabric cleaning machine o...	2.52	8.0	10	0.92	0.00	0.85	0.28	18
8160	Food and related products machine operators	2.50	10.0	9	1.00	0.00	0.88	0.39	93
8181	Glass and ceramics plant operators	2.46	10.0	10	0.92	0.08	0.86	0.58	12
8182	Steam engine and boiler operators	2.06	10.0	10	0.40	0.30	0.88	0.86	28
8183	Packing, bottling and labelling machine operators	2.50	10.0	10	1.00	0.00	0.75	0.23	26
8342	Earthmoving and related plant operators	2.50	4.0	10	0.00	0.00	0.88	0.96	70
8343	Crane, hoist and related plant operators	2.33	8.0	9	0.00	0.00	0.88	0.68	74
9112	Cleaners and helpers in offices, hotels and oth...	2.85	9.0	7	0.00	0.00	0.80	0.04	416
9321	Hand packers	3.10	10.0	7	1.00	0.00	0.75	0.24	66
9329	Manufacturing labourers not elsewhere classified	4.25	9.0	9	0.60	0.00	0.80	0.39	228
9333	Freight handlers	3.67	8.0	7	0.33	0.00	0.86	0.66	277
9334	Shelf fillers	2.71	9.0	6	0.00	0.00	0.78	0.31	13
9412	Kitchen helpers	3.01	9.0	8	0.00	0.00	0.88	0.03	157
9613	Sweepers and related labourers	3.68	4.0	7	0.00	0.00	0.80	0.35	26

Table 22: 4-digit ISCO codes for the 10^{th} decile of the Job Strain Intensity.

6 Conclusion

This research sheds light on the relationship between lifetime occupational demands and health outcomes measured during the later stages of life.

The SHARE dataset provides comprehensive 4-digit ISCO codes, facilitating precise assessment of occupational demands such as physical exertions (Deyaert et al. (2017)), psychosocial stress, exposure to carcinogens (Kroll (2015)), and task routines (Mihaylov and Tijdens (2019)) across each year of an individual's career. In particular, on-the-job physical expenditures are accurately quantified using the Metabolic Equivalent of Task (MET), allowing for a detailed measurement of physical exertion. The results unequivocally indicate that individuals engaged in physically demanding jobs experience significantly worse health. Specifically, an increase of one MET, which is roughly comparable to transitioning from a job like "Dental assistant and therapist" to "Hand packer," corresponds to an additional ageing effect of 2.33 years. The analysis reveals intriguing heterogeneity in gender differences, suggesting that the impact of physically demanding jobs on health is more pronounced for women than for men. Specifically, an increase of one MET has an effect that is nearly double the overall effect, resulting in 4.63 additional years of ageing. This finding underscores the need for further investigation into the underlying factors and prompts the implementation of gender-specific policy considerations to address these disparities effectively.

These findings consistently persist across multiple health measures and remain robust even after considering a comprehensive set of confounding variables. We thoroughly discuss all potential sources of endogeneity that could influence self-selection into specific occupations and introduce a complete set of controls to effectively address potential biases arising from omitted variables. Specifically, these control variables encompass childhood conditions, current socio-economic conditions, healthy habits, job characteristics, and exposure to other job demands such as psychosocial stress, carcinogenic agents, and task routines. In addition to the main analysis, we conduct several additional robustness checks to reinforce the validity of the observed effects. Among these checks, we consider Oster bounds Oster (2019), Causal Forest estimation Athey et al. (2019), and Shapley values Roth (1988). Furthermore, we utilise the LASSO estimator and the detailed job-specific tasks available at the 4-digit ISCO code level to propose a novel data-driven approach to constructing a new Job Strain Intensity variable. This variable incorporates unobserved job characteristics that are typically more challenging to identify. Remarkably, even after considering the Job Strain Intensity measure, the effect of MET remains consistently strong. Additionally, the impact of the Job Strain Intensity variable is noteworthy, as an increase of one standard deviation is associated with an additional ageing effect of 1.24 years even after controlling for the vast set of controls.

In addition, the novel method is able to effectively identify specific tasks (and their corresponding 4-digit ISCO codes) that significantly impact health in older age. Specifically, we detect the five most harmful specific job tasks: "Construction and restoration," "Preparing, cooking, serving meals," "Sweeping, vacuum-cleaning, polishing, and washing," "Repair/maintenance," and "Operating heavy-duty equipment". Next, we use the Job Strain Intensity measure to detect the 4-digit ISCO codes that are more likely associated with adverse job conditions.

In conclusion, this study can be a vital resource for policymakers and employers, offering critical insights into the implications of on-the-job physical activity and specific job tasks on the health of workers. By recognising and addressing the challenges posed by physically demanding occupations, we can strive to create more equitable and supportive work environments for individuals, ultimately enhancing their overall well-being and productivity. Moreover, building upon the existing literature, this study raises pertinent questions about the fairness of the implementation of interventions regarding statutory retirement ages and the impact on the equality of the pension system (Deeg et al. (2021); Marcus et al. (2022)). However, by identifying specific job positions at the 4-digit ISCO code level that are more likely to affect health, targeted retirement terms can be developed to effectively address these concerns. Again, the identification of tasks and job positions at a very granular level related to worse health allows policymakers to focus on crafting precise safety regulations in the workplace. Additionally, pinpointing the most hazardous tasks can guide investments towards automation, with the aim of mitigating the detrimental impact on health and enhancing overall workplace safety.

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Appendix

Example of Elementary Occupation ISCO codes

9 Elementary Occupations
91 Cleaners and Helpers
911 Domestic, Hotel and Office Cleaners and Helpers
9111 Domestic Cleaners and Helpers
9112 Cleaners and Helpers in Offices, Hotels and Other Establishments
912 Vehicle, Window, Laundry and Other Hand Cleaning Workers
9121 Hand Launderers and Pressers
9122 Vehicle Cleaners
9123 Window Cleaners
9129 Other Cleaning Workers
92 Agricultural, Forestry and Fishery Labourers
921 Agricultural, Forestry and Fishery Labourers
9211 Crop Farm Labourers
9212 Livestock Farm Labourers
9213 Mixed Crop and Livestock Farm Labourers
9214 Garden and Horticultural Labourers
9215 Forestry Labourers
9216 Fishery and Aquaculture Labourers
93 Labourers in Mining, Construction, Manufacturing and Transport
931 Mining and Construction Labourers
9311 Mining and Quarrying Labourers
9312 Civil Engineering Labourers
9313 Building Construction Labourers
932 Manufacturing Labourers
9321 Hand Packers
9329 Manufacturing Labourers Not Elsewhere Classified
933 Transport and Storage Labourers
9331 Hand and Pedal Vehicle Drivers
9332 Drivers of Animal-drawn Vehicles and Machinery
9333 Freight Handlers
9334 Shelf Fillers
94 Food Preparation Assistants
941 Food Preparation Assistants
9411 Fast Food Preparers
9412 Kitchen Helpers
95 Street and Related Sales and Services Workers
951 Street and Related Services Workers
9510 Street and Related Services Workers
952 Street Vendors (excluding Food)
9520 Street Vendors (excluding Food)
96 Refuse Workers and Other Elementary Workers
961 Refuse Workers
9611 Garbage and Recycling Collectors
9612 Refuse Sorters
9613 Sweepers and Related Labourers
962 Other Elementary Workers
9621 Messengers, Package Deliverers and Luggage Porters
9622 Odd-job Persons
9623 Meter Readers and Vending-machine Collectors
9624 Water and Firewood Collectors
9629 Elementary Workers Not Elsewhere Classified

Table 23: ISCO classification of the ”9 Elementary Occupations” major group. 2-digit codes are the sub-major groups, 3-digit codes are the minor groups, and the 4-digit codes are the unit groups.

Job stressors in decile

To rule out the case that the effects are simply driven by the fact occupational stressors are measured in a different way, we harmonize them according to deciles.

	(1)	(2)	(3)	(4)	(5)	(6)
	sphus	sphus	sphus	sphus	sphus	sphus
MET decile	0.048***	0.047***	0.035***	0.027***	0.024***	0.023***
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
Psychosocial stress decile	-0.012***	-0.009**	-0.009**	-0.006	-0.006	-0.010
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.006)
Carcinogenic agents' exposure decile	0.008	0.013***	0.011**	0.007	0.005	0.006
	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)	(0.006)
Routine manual decile	0.016***	0.010***	0.006*	0.002	0.002	0.004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Routine cognitive decile	0.007	0.010**	0.008**	0.007*	0.004	-0.001
	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
Constant	2.859***	-1.576	0.191	1.172	0.875	3.432***
	(0.050)	(2.793)	(2.510)	(2.524)	(2.594)	(0.362)
Socio-demo		✓	✓	✓	✓	✓
Child			✓	✓	✓	✓
Socio-econ				✓	✓	✓
Job					✓	✓
Habits						✓
Observations	36,946	36,946	29,988	29,988	29,917	20,325
R-squared	0.025	0.117	0.146	0.160	0.177	0.241

Table 24: OLS regression of "Self-perceived poor health" on occupational stressors in deciles. Standard error clustered at the 4-digit ISCO code level.

Tasks detected by LASSO

-	Blow and pack insulating	Forest & field measurement	Receiving & giving on &
	Adjusting & maintaining eq	Gardening general	Receiving & verifying &
	Advising on selling goods	Grading mixing tobacco t	Removing asbestos & mould
	Animal care	Hammering nails	Removing soot
	Appraising	Heavy cleaning	Repair & maintenance & li
	Arts and crafts	Inspecting buildings &	Repair & maintenance & mo
	Assembling & modifying in	Inviting tenders	Researching & verifying & a
	Bookkeeping	Labeling	Roofing
	Butchering animal	Leveling floor	Routine lab tests
	Carpentry light	Levers forklift	Scanning recording wrapp
	Carpentry moderate	Machining & working sheet	Selecting & modifying &
	Carpet cleaning	Maintenance & repairs	Setting up & operating
	Catwalk & acting on stage	Making bed & cleaning bat	Shovelling
	Chemical treatment	Making calculations	Snow shoveling & manual
	Cleaning kitchen & bathroom	Masonry & concrete	Software testing
	Cleaning kitchen including	Monitoring equipment & p	Sorting & recycling mater
	Cleaning stone walls heavy	Nursing assistant nursing	Stimulating discussion
	Cleaning windows	Obtaining information	Stock control
	Clearing up rubbish & empt	Operating & coordinating	Stone quarrying
	Collecting mineral sample	Operating heavy-duty equ	Sweeping & vacuum cleaning
	Collecting samples & prepare	Operating light equipment	Tailoring by hand
	Construction & restoration	Operating sewing machine	Tailoring light
	Coordination at workplace	Painting & varnishing &	Teaching kindergarten &
	Data collection & quali	Patrolling & standing &	Training animals
	Delivering postal mail	Photography	Unloading truck
	Designing & preparing b	Physical care & bathing &	Unpacking and storing su
	Driving train tram bus	Planting crops	Vehicle maintenance repa
	Electrical work	Plumbing	Walking & carrying heavy &
	Erecting & dismantling m	Preparing medicine dosages	Washing by hand & moderate
	Estimating size & shape	Preparing wall areas	Weighing goods & issue
	Farming light effort	Preparing & cooking & serv	Wheelbarrowing
	Feeding felled trees int	Preparing & planting & and	identifying & reporting &
	Filling boxes	Purchasing & ordering fo	
		Raking lawn or leaves	

Table 25: Harmful tasks detected by LASSO estimator see section 5.4.