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Bastian Ravesteijn, Hans van Kippersluis, Eddy van Doorslaer*

Abstract

Although it seems evident that occupation affects health, effect estimates are scarce. We use a job characteristics matrix linked to German longitudinal data spanning 26 years to characterize occupations by their physical and psychosocial burdens. Employing a dynamic model to control for factors that simultaneously affect health and selection into occupation, we find that manual work and low job control both have a substantial negative effect on health that gets stronger with age. The effects of late-career exposure to high physical demands and low job control are comparable to a health deterioration due to aging 12 and 19 months, respectively.

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1 Introduction

Average health and life expectancy differ substantially across occupational groups (Marmot et al., 1991; Case and Deaton, 2005). For example, manual workers in the US are 50 percent more likely to die within a given year than workers in managerial, professional and executive occupations (Cutler et al., 2008). Mackenbach et al. (1997); Kunst et al. (1998) report that the mortality rate for manual workers in eight European countries is higher than for non-manual workers throughout the age distribution, and this gap has widened over time (Mackenbach et al., 2003). For the Netherlands, Ravesteijn et al. (2013) find a strong gradient in self-assessed health by occupational class—particularly at an older age—and note that 20 percent of elementary workers[1] at the age of 60 have exited the workforce into disability, as opposed to eight percent of workers in occupations that require academic training.

Apart from occupation exerting a causal effect on health, the strong correlation between occupation and health may stem from reverse causality, with health constraining occupational choice. Moreover, individuals in different occupational groups can differ in other observed and unobserved "third factors" that influence health. For example, manual workers may have lower educational levels or possess different genetic predispositions as compared with nonmanual workers. Both reverse causality and third factors may lead to selection effects: people with good health prospects are selected into certain types of occupations. As a result, the magnitude of the association between occupation and health may differ from the magnitude of the causal effect of occupation on health.

In this paper, we aim to assess the extent to which the observed association is due to causation that runs from occupation to health. From a fairness perspective, health disparities that result from occupational stressors may be socially undesirable. Policymakers may want to distinguish between health disparities resulting from free choice behavior, such as smoking or drinking, and from occupational stressors that can only be chosen from a heavily constrained choice set.

From a productivity perspective, policymakers and employers are interested in

[1]Elementary occupations consist of simple and routine tasks which mainly require the use of hand-held tools and often some physical effort.

knowing which specific occupational characteristics are most harmful to health. For example, occupations with harmful ergonomic workplace conditions may simultaneously be characterized by low control possibilities at work, which may exert an independent effect on health. Consequently, improved knowledge of these separated effects might allow for efforts that are better-targeted at reducing sickness absenteeism and disability by adjusting specific labor conditions.

Many studies have documented strong associations between the type of occupation and health (see e.g. Kunst et al., 1999; Goodman, 1999). However, few of these studies attempt to obtain estimates of a causal effect, and those that do often focus on specific occupations or specific types of exposure to unhealthy circumstances (e.g. Bongers et al., 1990, who study back pain among helicopter pilots). The relationship between occupation and health has received surprisingly little attention in the economics literature, but interest in the topic has grown in recent years. Case and Deaton (2005) show that the self-reported health of manual workers is lower and declines more rapidly with age than that of non-manual workers. Choo and Denny (2006) report similar patterns for Canadian workers while controlling for a more extensive set of lifestyle factors and suggest that manual work has an independent effect on health over and above any differences in lifestyle across occupations. Using the longitudinal Panel Study of Income Dynamics (PSID), Morefield et al. (2012) estimate that five years of blue-collar employment predicts a four to five percent increase in the probability of moving from good health to poor health. However, as the authors acknowledge, these studies are limited in their ability to investigate the role of factors that may affect both selection into certain types of occupation and health itself.[2]

Using a three-digit occupational classification, Fletcher et al. (2011) combine information on the physical requirements of work and environmental conditions

[2]Apart from current occupation, a worker's entire occupational history is likely to affect current health. Thus, Fletcher and Sindelar (2009) use father's occupation during childhood and the proportion of blue-collar workers in the state as instrumental variables for first occupation and find that a blue-collar first occupation negatively affects self-assessed health. Kelly et al. (2012) question the statistical relevance of the two instrumental variables used in Fletcher and Sindelar (2009) and instead propose methods developed by Lewbel (2012) and Altonji et al. (2005) to investigate the causal effect of first occupation on health. They find that entering the labor market as a blue-collar worker raises the probabilities of obesity and smoking by four and three percent, respectively, which indicates that the effect of occupation on health may—at least in part—be transmitted through lifestyles.

taken from the Dictionary of Occupational Titles (DOT) with occupational information in the US Panel Study of Income Dynamics (PSID). Their aim is to estimate the health impact of five-year exposure to physical and environmental conditions. They control for first-observed health and five-period lagged health in their empirical model and report negative health effects of physical requirements and environmental conditions on health for women and older workers but not for men and nonwhite women and strong negative effects of environmental conditions for young men but not for young women. Fletcher et al. (2011) acknowledge that the potential endogeneity of occupation and occupational change does not allow for a causal interpretation with respect to their random effects estimates. Reverse causality and unobserved third factors may lead to biased estimators, and it is impossible to disentangle the contributions of physical and psychosocial occupational stressors in their approach.

In this study, we aim to overcome these limitations in two ways. First, we estimate a fixed effects model that controls for lagged health to estimate the effect of exposure to occupational stressors in the previous year on current health. Based on a theoretical model of occupation and health over the life cycle, we derive mechanisms of health-related selection into occupation, we show how our econometric estimators relate to the structural parameters, and we explicitly formulate conditions under which our estimates allow for a causal interpretation. We argue that in this case, with panel data spanning 26 years and where credible sources of exogenous variation in occupation appear to be non-existent, our model provides the most promising estimates of the effect of occupation on health. Our alternative formulation of the Grossman (1972) model illustrates its implicit assumptions about the decaying effect of past shocks and health investment on current health. These insights are informative for anyone attempting to provide theoretical foundations for an econometric dynamic panel data model.

Second, we argue that blue-collar and manual occupations are both more physically demanding and often characterized by low psychosocial workload. Previous studies have often characterized occupation with a binary indicator of manual versus nonmanual occupation or have focused only on the manual aspects of occupation. This approach left the contributions of the various ergonomic and psychosocial stressors unseparated and made it difficult to draw clear policy conclusions. By linking Finnish data on occupational stressors to individual-level longitudinal German data, we are able to unravel the health effects of job characteristics in great detail. The US DOT instrument, for instance, captures physical requirements and environmental conditions but lacks information on psychosocial workplace conditions.

Our findings suggest that approximately 50 percent of the association between physical demands at work and self-reported health stems from the causal effect of physical demands. Selection accounts for the remaining 50 percent. The average immediate effect of a one standard deviation increase in the degree of manually handling heavy burdens (e.g., from a wholesale worker to a plumber or from a mail sorter to a bricklayer) is comparable to the effect of aging five months, and the effect increases with age. A lower degree of control over daily activities at work (e.g., kitchen assistant versus cook, or nurse versus physiotherapist) is harmful to health at older ages but not at younger ages. Assuming that the coefficient of lagged health captures the decay rate of past choices and shocks, we estimate that exposure to a one standard deviation increase in handling heavy burdens between the ages of 60 and 64 leads to a health deterioration that is comparable to aging 16 months. The estimated effect of exposure to low job control between the ages of 60 and 64 is comparable to aging 23 months.

The remainder of this paper is organized as follows: Section 2 discusses the theoretical relationship between occupation and health. Section 3 introduces the German Socioeconomic Panel. Section 4 outlines our empirical approach to estimating the effect of manual work on health. Section 5 presents the results. Section 6 discusses how our results relate to the literature and concludes.

2 Occupation and health over the life cycle

In the economics literature, health is treated as a durable capital stock that depreciates with age and can be increased with investment (Grossman, 1972). The age-related health depreciation rate is exogenous, but an individual can invest in his health by purchasing preventive and curative medical care. The effect of behavior on health can be positive or negative. Occupational choice can be understood as a form of health disinvestment/erosion: an individual chooses an occupation that is characterized by a set of potentially harmful occupational stressors (Case and Deaton, 2005; Galama and van Kippersluis, 2010). Occupations with more harmful characteristics may yield higher earnings than other less harmful occupations in the choice set of the individual, which is known as the compensating wage differential (Smith, 1974; Viscusi, 1978). The additional earnings may be used to partially offset the detrimental effect of work on health by investing in health or to increase consumption. This economic paradigm is useful in detecting the sources of health-related selection into occupation.

These insights are embedded in a theoretical model of an individual maximizing the expected present value of lifetime utility, which is derived from consumption c and health h, by choosing levels of consumption c, occupational stressors in vector $\mathbf{o}$, and health investment m. Each occupation is characterized by physical and psychosocial occupational stressors that tend to be clustered, i.e., occupations with low psychosocial workload are often characterized by high physical demands. Future utility is discounted at discount rate β. The information set $\mathcal{I}$ includes endowments e and permanent health h_p, all state and choice variables up to time t, and all future values of the aging rate, but not future unanticipated health shocks η.

$$max_{\{c_{t+j},\mathbf{o}_{t+j},m_{t+j}\}_{j=0}^{T-t}} E\left[\sum\nolimits_{j=0}^{T-t} \beta^j u(c_{t+j}, h_{t+j})|\mathcal{I}_t\right] \tag{1}$$

The health production function depends on (i) characteristics and circumstances that remain constant over time that are embodied by permanent health $h_p = f(e)$, which is a function of endowments and reflects all circumstances and personal characteristics that remain constant over the life cycle; (ii) anticipated health deterioration due to aging a; (iii) a vector of occupational characteristics $\mathbf{o}$; (iv) medical investment m; and (v) exogenous health shocks η. The effect of occupational characteristics on health, $\boldsymbol{\gamma}_o$, is nonpositive, and $0 \leq \theta \leq 1$ reflects diminishing marginal benefits to health investment. Total lifetime T is exogenous and known to the individual, and the effects of occupational stressors, health investments and shocks are assumed to decay at the same rate ϕ, which lies between

0 and 1.

$$h_{t+j} = h_p + \sum\nolimits_{k=2}^{t+j} \left(a_k + \phi^{t+j-k}(\boldsymbol{\gamma}_{\mathbf{o}}' \mathbf{o}_{k-1} + \gamma_m m_{k-1}^{\theta} + \eta_k)\right) \tag{2}$$

Expenditures on consumption and health investment, at prices p_c and p_m, respectively, should not exceed the net value of wage earnings. The individual can lend and borrow at real interest rate r, but he must repay any remaining debt at the end of his life. Wage w is a function of (i) current occupational choice $\mathbf{o}$, (ii) current health h, and (iii) endowments e.

$$s.t. \sum\nolimits_{k=1}^{T} (p_c c_k + p_m m_k) \leq \sum\nolimits_{k=1}^{T} (1+r)^{k-1} w(\mathbf{o}_k, h_k; e) \tag{3}$$

Consumption, health investment and occupational choice are chosen by equating marginal benefit with marginal cost. The marginal utility of consumption is equal to the shadow price of income λ multiplied by the price of consumption.

$$\frac{\partial u_t}{\partial c_t} = \lambda p_c \tag{4}$$

For each occupational attribute o_l in vector $\mathbf{o}$, the marginal benefit of occupational stress is represented by the product of λ and the instantaneous wage premium. The marginal cost includes the marginal deterioration of health in all future periods multiplied by (i) the discounted marginal utility of future health and (ii) the product of λ and the present value of the marginal wage returns to future health.

$$\lambda \frac{\partial w_t}{\partial o_{t,l}} = -\sum\nolimits_{j=1}^{T-t-1} \frac{\partial h_{t+j}}{\partial o_{tl}} \left[\beta^j \frac{\partial u_{t+j}}{\partial h_{t+j}} + \lambda \left(\frac{1}{1+r}\right)^j \frac{\partial w_{t+j}}{\partial h_{t+j}}\right] \quad \forall l \tag{5}$$

Health investment is the 'mirror image' of occupational choice. The marginal benefit (the product of the marginal effect of health investment on health and both the discounted marginal utility of health and the marginal wage returns to health in all future periods) is equated with marginal cost (the product of the shadow price of income and the price of medical care).

$$\sum_{j=1}^{T-t-1} \frac{\partial h_{t+j}}{\partial m_t} \left[\beta^j \frac{\partial u_{t+j}}{\partial h_{t+j}} + \lambda \left(\frac{1}{1+r} \right)^j \frac{\partial w_{t+j}}{\partial h_{t+j}} \right] = \lambda p_m \qquad (6)$$

The theoretical framework shows how an individual takes the future consequences of his decisions into account while deciding on the optimal levels of harmful occupational stressors. Three insights from the theory are particularly noteworthy. First, both time-invariant initial endowments e—in the form of, for example, physical ability, intelligence or taste for adventure—and time-varying factors such as health shocks η—e.g. a car accident or the onset of a disease— may influence both occupational choice and health status through (i) the marginal utility of health, (ii) the marginal wage returns to health, and (iii) the shadow price of income λ. This finding indicates that workers may select themselves into certain types of occupations depending on exogenous factors that directly influence health. The observed health differences across occupational classes should therefore not be interpreted as evidence of a causal effect of occupation on health.

Second, in contrast to exogenous sources of health-related selection into occupation, such as endowments and shocks, individuals choose their levels of health investment. Health investment may be correlated with occupational choice because (i) exogenous factors influence both health and occupational choice and (ii) workers may choose to offset occupation-related health damage by investing in health (e.g., a bricklayer may seek physiotherapeutic treatment for his back pain, or a manager may take yoga classes to improve his mental well-being).

Third, the relationship between work and health may change over the life cycle. This change can occur for three reasons. First, as equation 6 illustrates, the expected wage returns on health investment decrease as the individual approaches retirement age, which implies that individuals have fewer incentives to offset occupational damage to health by medical investment.[3] Second, $\boldsymbol{\gamma_o}$ may change over the lifetime, for example if health at older ages is more susceptible to wear and tear at the workplace. Third, the marginal effect of health repair may decrease with age to such an extent that full health repair is no longer feasible at older

[3]However, a model that endogenizes length of life as a function of health can explain an increase in medical investment at older ages.

ages.[4]

In sum, our empirical identification strategy should (i) account for factors that can influence selection into type of occupation and may also be related to health, (ii) address how behavioral adjustments that affect health may coincide with occupational choice, and (iii) accommodate the changing relationship between occupation and health over the life cycle.

3 Occupational stressors and the German Socioeconomic Panel

The German Socioeconomic Panel (SOEP) is a representative household survey that began in 1984. We use data from the 26 subsequent annual waves. Respondents are followed over multiple waves, but the panel is unbalanced because many respondents enter the sample after the 1984 or leave the sample before 2009. The sample is restricted to 196,935 person-wave observations, for which we observe employment in the previous year, health in the previous and in the current year, and educational attainment. We drop individuals who are younger than 16 or older than 65 years of age.

Respondents were asked to rate satisfaction with their own health on an integer scale from 0 to 10, which we refer to as self-assessed health (SAH). SAH will be the dependent variable throughout the paper. Occupational titles were coded into the International Standard Classification of Occupations of the OECD (ISCO-88). This classification consists of 311 occupational classes that were grouped into nine ranked major occupational groups by the OECD, excluding the military. On the basis of the OECD classifications, we define white-collar workers as legislators, senior officials, managers, professionals, technicians, associate professionals, and clerks. We define blue-collar workers as service workers and shop and market sales workers, skilled agricultural and fishery workers, craft and related trades workers, plant and machine operators, assemblers, and workers in elementary occupations. These definitions are consistent with the distinction between manual and non-

[4] Our model does not incorporate real-world labor market rigidities, but such rigidities may also prevent individuals from switching occupations at older ages to optimize their exposure to occupational stressors.

manual work of Case and Deaton (2005). According to these definitions, we have a total of 103,986 person-wave observations for white-collar occupations and 92,949 observations for blue-collar occupations.

Figure 1 graphs age-predicted SAH for blue-collar and white-collar workers. On average, blue-collar workers report better health at younger ages, whereas the opposite is true after the age of 28. SAH decreases for both blue-collar and white-collar workers over most of the age range but increases after the age of 57. However, one should keep in mind that these patterns only reflect the SAH ratings of those who are employed.[5] Consistent with Case and Deaton (2005), we find that the health decline in the pooled sample associated with age is much steeper among blue-collar than white-collar workers, which begs the question as to why blue-collar workers' health deteriorates more rapidly than that of white-collar workers. Panel A of table 1 shows that the average SAH score for those who work

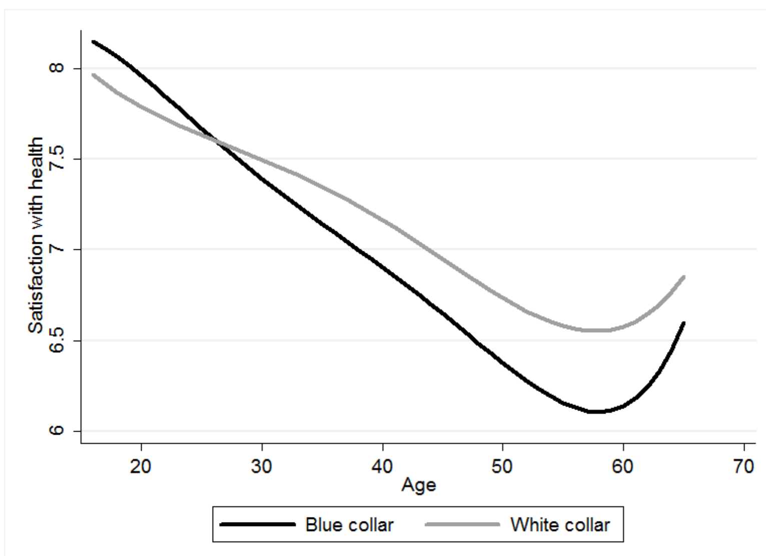


Figure 1: Health for blue- and white-collar workers.

Predicted satisfaction with health for blue- and white-collar workers over the life cycle. Source: SOEP.

is 6.96, and on average blue-collar workers report worse health (6.88) than white-

[5] At older ages, unhealthy workers exit out of employment, whereas healthy workers remain employed.

Table 1: German Socioeconomic Panel.

	SAH	Age	Female	Schooling	Earnings	Observations
A. Baseline sample						
All workers	6.96	41.06	.44	12.00	1,414	196,935
	(2.05)	(11.49)		(2.69)	(1,069)	
White collar	7.02	42.15	.52	13.27	1,677	103,986
	(1.99)	(11.11)		(2.83)	(1,278)	
Blue collar	6.88	39.83	.35	10.59	1,110	92,949
	(2.12)	(11.78)		(1.62)	(633)	
B. Individuals who were employed in at least nine annual waves						
All workers	6.88	42.37	.41	11.97	1,475	111,802
	(1.99)	(10.23)		(2.64)	(897)	
White collar	6.95	43.08	.50	13.16	1,690	59,931
	(1.95)	(9.92)		(2.78)	(1,036)	
Blue collar	6.82	41.55	.31	10.59	1,223	51,871
	(2.03)	(10.51)		(1.58)	(611)	

SAH, age, female proportion, years of schooling and monthly labor earnings in the German Socioeconomic Panel. Each wave is viewed as a separate observation. Standard deviations are in parentheses. Sample sizes for income are 181,216 and 128,780 for panels A and B, respectively. Source: SOEP.

collar workers (7.02).[6] Blue-collar workers are slightly younger and less likely to be female, on average, compared with white-collar workers. The average years of schooling among blue-collar and white-collar workers are 10.59 and 13.27 years, respectively. If we disregard censoring, average net monthly labor earnings are €1,677 for white-collar workers and €1,110 for blue-collar workers.

Panel B of table 1 shows that the average age in the restricted sample of individuals who were observed in at least nine waves is approximately one year higher than in the full sample. Average health and the proportion of women are slightly lower. The full and restricted samples are similar in terms of education and (blue-collar) employment, but average earnings in the restricted sample are slightly higher.

[6]Health worsens from the top to the bottom of the OECD occupational ladder: 23 percent of legislators, senior officials and managers rate their health with a five or less, as opposed to 31 percent of elementary workers, and 49 percent of legislators, senior officials and managers rate their health with at least an eight, as opposed to 42 percent of elementary workers. This pattern is monotonic across the nine ranked major OECD occupational groups.

Sample sizes per wave range from 4,647 in 1989 to 10,714 in 2001. Figure 2 shows that we observe 28,454 individuals for at least one period and that 9,110 individuals are observed for at least nine periods. Both the full sample and the restricted sample refer to (not necessarily consecutive) person-wave observations for individuals who were working in the previous period and for whom we observe age, years of schooling, and health in the previous and current periods.

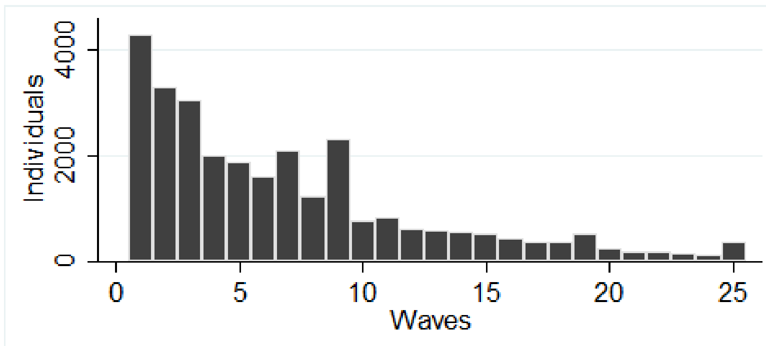


Figure 2: Number of individuals by the number of waves.

Each bar shows the number of individuals in the sample for the respective total number of (not necessarily consecutive) waves. Source: SOEP.

Although the distinction between blue-collar and white-collar occupations helps us to understand health differences across broad occupational groups, it does not allow us to identify which aspects of occupational stressors associated with blue-collar occupations matter the most. In Finland, a Job Exposure Matrix (FINJEM) was constructed from a detailed survey on occupational stressors that maps occupational titles into three measures of occupational stressors (Kauppinen et al., 1998; Lavoué et al., 2012): (i) the manual handling of burdens, (ii) control possibilities at work, and (iii) psychosocial workload. Such information on occupational stressors in Germany is unavailable,[7] and therefore, we use the FINJEM to map approximately 360 different occupational titles in the SOEP. These titles are mapped into (ordinal) measures of occupational stressors. This involves the assumption that the relationship between OECD-classified occupations and occupational stressors in Finland and Germany is similar. Information on the manual

[7]The German Qualification and Career Survey only includes information on analytical tasks, manual tasks, and interactive tasks, whereas we are interested in physical and psychosocial stressors.

handling of burdens by occupations is available for the period between 1998 and 2006, and the psychosocial indicators are available for the period between 1985 and 1994. The variables do not differ between years, and we assume that the ordinal relationship with respect to the occupational stressors between occupations remained unchanged throughout the sampling period.

Whereas in the analysis, we use the mapping of occupational stressors to individual job titles, table 2 shows the exposure of the nine major OECD occupational groups in the SOEP to the three occupational stressors in the FINJEM for illustrative purposes. The variable that measures manual handling of burdens takes one of 56 different values and is demeaned and divided by its standard deviation. The two psychosocial variables can take two values: high or low.

Two important observations can be made. First, blue-collar occupations are characterized not only by more frequent manual handling of heavy burdens compared with white-collar occupations but also by lower psychosocial workload, which is often ignored in the literature. Control possibilities vary across occupations, but there is no clear pattern if we move up the occupational ladder.

Second, there is ample variation in occupational characteristics even within the major occupational groups. Even though blue-collar workers are generally more likely to work under more demanding ergonomic conditions and lower psychosocial workload compared with their white-collar counterparts, this may not necessarily be the case for many specific occupations. A simple division into blue-collar or white-collar occupations therefore neglects the considerable heterogeneity within these groups and the clustering of occupational stressors. In the remainder of this paper, we will use both the blue-collar/white-collar distinction and the variation on the basis of the three occupational stressors across the 360 occupational titles in the FINJEM to estimate the effects of occupation on health.

4 Estimation of the effect of occupational stressors on health

We estimate the structural parameter $\boldsymbol{\gamma}_{\mathbf{o}}$ in equation 2, which refers to the health effects of exposure to occupational stressors $\mathbf{o}$ in the previous year. Note that

Table 2: Occupational stressors across the major ISCO occupational groups.

	Manual handling of burdens, percentage above mean	Percentage with low job control	Percentage with high psychosocial workload	Observations
Legislators, senior officials and managers	24	10	100	11,270
Professionals	6	8	100	28,682
Technicians and associate professionals	18	18	75	40,592
Clerks	9	4	55	23,442
Service workers and shop/market sales workers	90	11	67	20,530
Skilled agricultural and fishery workers	100	0	0	2,737
Craft and related workers	76	9	22	37,011
Plant and machine operators and assemblers	87	37	16	18,232
Elementary occupations	100	3	11	14,439

Percentages reflect the proportion above the mean for manual handling of burdens, the proportion exposed to low job control and high psychosocial workload. Manual handling of burdens is an index, and job control and psychosocial workload are binary variables. White-collar occupations are above the dashed line, and blue-collar occupations are below the dashed line. Source: SOEP, FINJEM.

the one-period lag of the health production function (equation 2), which includes permanent health h_p, the health effects of aging a, health investment m and shocks η, is:

$$h_{t+j-1} = h_p + \sum\nolimits_{k=2}^{t+j-1} \left(a_k + \phi^{t+j-1-k}(\boldsymbol{\gamma}_{\mathbf{o}}'\mathbf{o}_{k-1} + \gamma_m m_{k-1}^{\theta} + \eta_k)\right) \tag{7}$$

Substituting equation 7 into equation 2, we obtain:

$$h_{t+j} = (1-\phi)\left(h_p + \sum\nolimits_{k=1}^{t+j-1}(a_k)\right) + a_{t+j} + \boldsymbol{\gamma}_{\mathbf{o}}'\mathbf{o}_{t+j-1} + \gamma_m m_{t+j-1}^{\theta} + \phi h_{t+j-1} + \eta_{t+j} \tag{8}$$

Switching to individual notation and demeaning the covariates to eliminate the time-invariant factors, we obtain a fixed effects within estimator:

$$h_{i,t+j} - \bar{h}_i = \phi(h_{i,t+j-1} - \bar{h}_i) + \boldsymbol{\gamma}_{\mathbf{o}}'(\mathbf{o}_{i,t+j-1} - \bar{\mathbf{o}}_i) + \boldsymbol{\delta}'(\mathbf{x}_{i,t+j} - \bar{\mathbf{x}}_i) + \varepsilon_{i,t+j} \tag{9}$$

where any unobserved heterogeneity that is constant over time and may be correlated with occupation (such as permanent health h_p in equation 2) is eliminated: $(1-\phi)h_p - (1-\phi)\bar{h}_p = 0$. Coefficient ϕ of the demeaned one-period lag of health can be interpreted as the decay parameter through which occupational choice $\mathbf{o}$, health investment m, and unanticipated shocks η in period t-2 and earlier periods affect current health.

$\mathbf{x}$ is a vector of control variables consisting of age, age squared, age to the third power, and wave dummies to control for common time trends. We assume that the effect of age is smooth and can be approximated by an age polynomial of the fifth degree. A less flexible approximation of the age effect, such as only controlling for a linear term, would bias our estimates of $\boldsymbol{\gamma}_{\mathbf{o}}$ if health deteriorates more rapidly at older ages, and workers at older ages would be more or less likely to be exposed to certain occupational stressors.

The error term is $\varepsilon_{i,t+j} = \gamma_m(m_{i,t+j-1}^{\theta} - \bar{m}_i^{\theta}) + \eta_{i,t+j} - \bar{\eta}_i$, which implies two things. First, the ordinary least squares estimator of ϕ is biased because $h_{i,t+j-1}$ is correlated with $\bar{\eta}_i$ and $\bar{h}_i$ is correlated with $\eta_{i,t+j}$. Importantly, the estimator is consistent for large T (Nickell, 1981; Bond, 2002).

Second, the estimator of $\boldsymbol{\gamma}_{\mathbf{o}}$ is biased if occupation and health investment are correlated. The theory suggests that individuals simultaneously choose occupation and health investment such that the estimates should be interpreted as the sum of the structural effect of occupation and health investment decisions related to occupation.

Self-reported health, as measured on a five-point ordinal scale from poor to excellent, has been shown to be a reliable predictor of mortality and morbidity (e.g. Idler and Benyamini, 1997; Mackenbach et al., 2002). We use satisfaction with health (on a 0-10 integer scale) as a proxy for health, which exhibits more variation than the five-point measure. Ferrer-i Carbonell and Frijters (2004) and Frijters et al. (2005) show that for the variable that measures satisfaction with life on a ten-point scale, assuming ordinality or cardinality makes little difference, such that a linear specification is acceptable. Reporting heterogeneity because different subgroups may report the same objective health status differently (Lindeboom and van Doorslaer, 2004) is eliminated by the individual fixed effect to the extent that it is time-invariant.

Our estimates are based on within-individual variations in occupational stressors and health over time. We include individuals for whom we observe occupation in the previous year and health in the current year, which implies that our sample selection criterion is that individuals should have been working in the previous year. Thus, we estimate the occupational effect on the working population only. However, note that even if individuals do not work in the current period, we still estimate the effect of occupation in the previous period on health if current health is observed. In our sample, blue-collar workers are approximately three percent more likely than white-collar workers to be out of work in the next period. Our results should be interpreted as the average treatment effect on the working population. The average effect may be stronger in countries in which unhealthy blue-collar workers are more likely to remain employed.

A related issue is attrition due to mortality or nonresponse. We argue that health-related attrition—if present—will lead to a bias toward zero of our estimators if individuals with the highest vulnerability to occupation-related health deterioration are more likely to suffer from attrition. We find that the likelihood of attrition is at most one percent higher for blue-collar workers than for white-collar workers in our sample. Our estimates should therefore be interpreted as a lower bound on the true effect of occupational stressors.

5 Results

5.1 Main results

Table 3 shows the main results for six different models, where we first present results for a dichotomous indicator for blue-/white-collar occupations (columns 1 to 3) and then for occupation as characterized by three occupational stressors (columns 4 to 6). To understand the order of magnitude of the coefficients, note that the average health deterioration of growing one year older (obtained from an individual fixed effects regression of satisfaction with health on age) is -.0636 (.0008) in our sample.

The bivariate association in column 1 between satisfaction with health and blue- or white-collar occupation in the previous year shows that blue-collar workers are in worse health and that the size of this health gap is similar to the average effect of aging 25 months, which is a sizable and economically meaningful difference. Column 2 shows the results for the model described by equation 9. Much of the association appears to be driven by health-related selection into blue-collar occupations because the estimate of the effect is -.0376 (.0171) compared with -.1430 (.0091) in column 1. We conclude that the health effect of exposure to a blue-collar occupation in the previous year is comparable to the average health effect of aging six months.

We add an interaction between age and blue-collar work in column 3 of table 3 to investigate whether the causal effect of blue-collar employment differs with age. The coefficient of the dummy variable in the first row of column 3 refers to the hypothetical effect of blue-collar employment at the age of zero. The coefficients of the interaction term in the second row indicate that blue-collar employment becomes harmful to health at older ages and that this effect increases with age.

Column 4 breaks down occupation into three dimensions of occupational stressors: manual handling of heavy burdens—demeaned and divided by its standard deviation—job control, and psychosocial workload in the preceding year. The latter two dimensions are binary variables. Manual handling of burdens and low

Table 3: Results.

	Associations for blue/white collar	FE & LDV for blue/ white collar	FE & LDV for blue/white collar and age interactions	Associations for stressors	FE & LDV for stressors	FE & LDV for stressos and age interactions
	(1)	(2)	(3)	(4)	(5)	(6)
Blue-collar at t-1	-.1430*** (.0093)	-.0376** (.0177)	.1326*** (.0510)			
Age × blue collar at t-1			-.0045*** (.0013)			
Manual handling at t-1				-.0559*** (.0051)	-.0281*** (.0091)	.0337 (.0264)
Job control at t-1				.0532*** (.0149)	-.0142 (.0218)	.1430** (.0696)
Workload at t-1				.0628*** (.0099)	.0064 (.0141)	-.0415 (.0457)
Age × manual handling at t-1						-.0016** (.0007)
Age × job control at t-1						-.0040** (.0017)
Age × workload at t-1						.0012 (.0011)
Health at t-1		.0985*** (.0032)	.0974*** (.0032)		.0975*** (.0032)	.0974*** (.0032)
Individual FE, fifth order age polynomial and wave dummies	✗	✓	✓	✗	✓	✓
Observations	196,935	196,935	196,935	196,935	196,935	196,935
R^2	.0012	.5647	.5647	.0012	.5647	.5648

Main results for satisfaction with health. FE refers to fixed effects estimation, and LDV refers to the inclusion of the lagged dependent variable. Panel-robust standard errors are in parentheses. * indicates significance at the 10 percent level, ** at the 5 percent level, and *** at the 1 percent level. Fixed effects specifications are obtained by subtracting individual averages for each regressor. The reference category for columns 1 to 3 is working in a white-collar occupation. Intercepts not shown. Source: SOEP, FINJEM.

job control are associated with worse health, whereas psychosocial workload is positively associated with health.

Given our theoretical model, we expect strong health-related selection into occupation that might drive these associations. Column 5 therefore shows estimates of the effects of these three occupational stressors according to the specification in equation 9, which controls for selection into occupation on the basis of time-invariant and time-varying factors. These results imply that approximately 50 percent of the negative association between manual handling of heavy burdens and health can be explained by selection, and our point estimate (-.0281) of the causal effect of a one standard deviation increase in manually handling heavy burdens is comparable to aging five months.

The estimates of the causal effects of psychosocial stressors (control possibilities at work and workload) in column 5 are not significantly different from zero. As we observed in table 2, psychosocial workload is higher among white-collar workers and lower among blue-collar workers (except for service, shop, and market workers). Socioeconomic factors, such as education, influence both occupational rank—and therefore workload—and health status, which leads to selection bias of the naïve estimator in column 4. A comparison of the point estimates for workload in columns 4 and 5 confirms that selection effects are important for psychosocial workload. The 95 percent confidence interval of the causal estimate [-.0213, .0341] lies well below the confidence interval of the association [.0435, .0822], which is likely caused by eliminating much of the omitted variable bias that plagues the results in column 3.

Column 6 shows that the effects on health of low job control and handling heavy burdens vary with age. The predicted health deterioration caused by a one standard deviation increase in handling heavy burdens is equal to zero at the age of 21. However, at the age of 61—four years prior to the statutory retirement age—the point estimate of the effect is comparable to aging 12 months ($.0337 - .0016 \times 61 = -.0658$). Low job control has a negative effect after the age of 35: being in a job with low instead of high job control at the age of 61 leads to a predicted health deterioration comparable with the effects of aging 19 months ($.1430 - .0040 \times 61 = -.1031$). We conclude that the effect of manual work and job control is age-dependent. The effect of the interaction of workload and age is not significantly different from zero, possibly because of our crude, dichotomous measure of workload or because workload is only important for a subset of occupations.

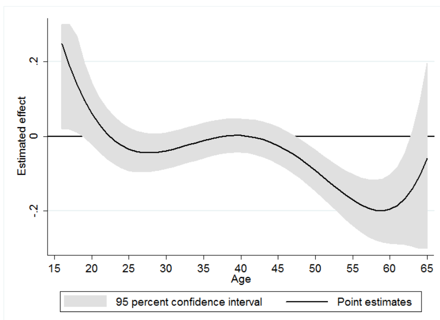
5.2 Cumulative effects

The health effects of past exposure to occupational stressors cannot simply be added together to obtain cumulative effects. Under demanding assumptions, we can compute cumulative health effects by using the estimated coefficient of the lagged dependent variable ϕ in equation 9. By assumption, ϕ is the uniform exponential decay rate at which past health investment, occupational stressors, and shocks affect current health in equation 2. The point estimates of ϕ in table 3 suggest that roughly ten percent of the occupation-related health deterioration in period t-2 persists in period t. Using the point estimates in column 6, the point estimate of health deterioration at the age of 65 caused by a one standard deviation increase in the manual handling of heavy burdens between ages 60 to 64 is $\sum_{k=60}^{64} .0974^{64-k}(.0337 - .0016 \times k) = -.0782$, which is comparable to the average health effect of aging nearly 14 months. Likewise, the point estimate of the effect of working in low-control occupations between the ages of 60 and 64 is -.1271, which is comparable to the effects of aging 24 months.

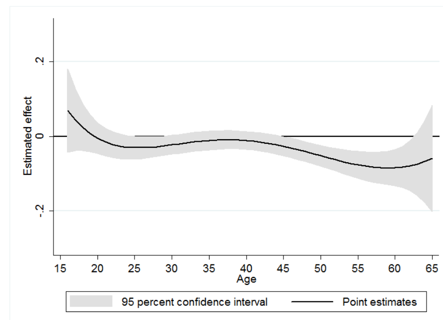
5.3 Vulnerability to occupational stressors over the life cycle

Figure 3 shows the results of two regression models that are similar to the specifications of columns 3 and 6 in table 3 but include additional interactions between the occupational variables and age up to the fifth power. Panel A shows the estimated next-period treatment effect of blue-collar versus white-collar occupations at different ages. Confidence intervals are computed using the delta method (Oehlert, 1992). The estimated next-period negative effect of blue-collar employment becomes statistically significant from the age of 48 onwards.

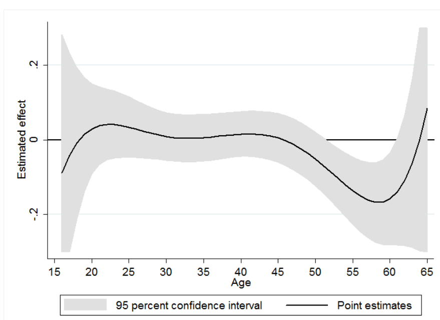
Caution is warranted when interpreting the estimates at the lower and upper end of the age distribution because of the low number of observations at young and old ages and the polynomial functional form of the treatment effect. Less



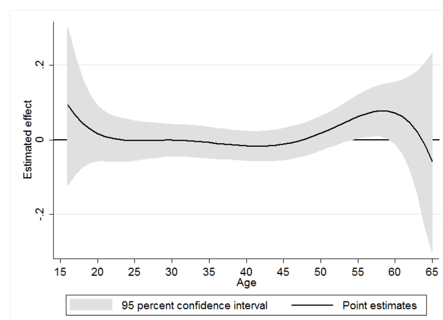
(a) Effect of blue-collar work.



(b) Effect of one s.d. increase in manual handling of burdens.



(c) Effect of low job control



(d) Effect of high work load

Figure 3: The effects of occupational stressors over the life cycle.

95 percent confidence intervals of the coefficients of the occupational stressors, computed using the delta method. Panels 3a, 3c, and 3d refer to the coefficients of binary variables. Source: SOEP, FINJEM.

than three percent of observations occur at ages below 20, and only two percent of observations occur at ages over 60.

Panels B, C, and D of figure 3 refer to estimated treatment effects obtained from the model in column 6 of table 3 with added interactions between each of the three occupational stressors and age up to the fifth power. The manual handling of burdens has a significant negative effect on workers aged 45 years and older. The estimated effect of manual handling of burdens seems small in absolute terms when compared with panels A or C, but one must bear in mind that the estimates in panel B refer to one standard deviation increases in the distribution of manual handling of burdens, whereas the estimates in panels A, B, and D refer to the effects of binary independent variables.

Panel C shows that the negative effect of low job control is significant for workers who are 52 years and older. The estimated negative effects in panels A, B, and C are strongest at approximately age of 60. We do not find evidence of a negative effect of high work load, which is revealed in panel D.

5.4 Robustness checks

The effect of occupational stressors potentially differs across gender because the type of stressors experienced and the vulnerability to certain stressors is likely to be different for men and women. Column 1 of table 4 shows that the direction and statistical significance of the estimates for the subsample of men are similar to the estimates in column 6 of table 3. The estimated effect of the manual handling of burdens in the subsample of women in column 2 does not increase with age, whereas the interaction effect of age and low job control is negative but insignificant. A regression without the age interactions gives a significant point estimate of -.0415 (s.e. .0142).

Individuals in different occupations may have different biological aging rates. We have assumed uniform aging effects in the preceding analyses. If the health of manual workers declines more rapidly regardless of their occupation, our results overestimate the harmful effects of physical stressors. In column 1 of table 4, we allow for different rates of aging by interacting an education dummy with a fifth-degree age polynomial. Our estimates are similar to our findings in table 3.

Table 4: Robustness.

	Men	Women	Control for education-specific aging trends	Only individuals with $T \geq 8$	FE	LDV
	(1)	(2)	(3)	(4)	(5)	(6)
Manual handling at t-1	.0855**	-.0440	.0325	.0499*	.0424	.0404***
	(.0355)	(.0402)	(.0268)	(.0296)	(.0267)	(.0149)
Job control at t-1	.2544***	.0314	.1437**	.2000***	.1490**	.0760*
	(.0894)	(.1117)	(.0696)	(.0774)	(.0702)	(.0456)
Workload at t-1	-.0543	.0518	-.0404	-.0187	-.0479	-.0586**
	(.0608)	(.0706)	(.0463)	(.0513)	(.0462)	(.0292)
Age × manual handling at t-1	-.0027***	.0001	-.0016**	-.0019***	-.0019***	-.0022***
	(.0009)	(.0099)	(.0007)	(.0007)	(.0007)	(.0004)
Age × job control at t-1	-.0061***	-.0020	-.0040**	-.0053***	-.0043**	-.0010
	(.0022)	(.0027)	(.0017)	(.0019)	(.0017)	(.0011)
Age × workload at t-1	.0014	-.0008	.0012	.0008	.0014	.0027***
	(.0015)	(.0017)	(.0011)	(.0013)	(.0011)	(.0007)
Health at t-1	.1118***	.0790***	.0973***	.1493***		.5422***
	(.0043)	(.0048)	(.0032)	(.0036)		(.0023)
Fifth order age polynomial and wave dummies	✓	✓	✓	✓	✓	✓
Fifth order age polynomial interacted with education	✗	✗	✓	✗	✗	✗
Individual FE	✓	✓	✓	✓	✓	✗
Education and gender	✗	✗	✗	✗	✗	✓
Observations	110,286	86,649	196,935	135,130	196,935	196,935
R^2	.5688	.5600	.5648	.5214	.5606	.3344

Robustness checks for satisfaction with health. FE refers to fixed effects estimation, and LDV refers to the inclusion of the lagged dependent variable. Panel-robust standard errors are in parentheses. * indicates significance at the 10 percent level, ** at the 5 percent level, and *** at the 1 percent level. Fixed effects specifications are obtained by subtracting individual averages for each regressor. Fourth column refers to sample of individuals who are observed in at least eight—not necessarily consecutive—waves. Intercepts not shown. Source: SOEP, FINJEM.

The estimator of the coefficient of the lagged dependent variable is consistent if the number of time periods in the sample goes to infinity. Our sample spans 26 years and is unbalanced because it includes individuals who are observed for a smaller number of waves. We repeat our analysis for a subsample of 10,373 individuals who have been employed for at least eight of the 26 years to counter the downward bias of the estimator of the lagged dependent variable that plagues short panels (Bond, 2002). The number of person-wave observations drops from 196,935 in our baseline sample to 135,130 in column 2 of table 4. The coefficients of the (age-interacted) occupational stressors are similar to those in our baseline specification. However, the coefficient of lagged health is now larger, suggesting that past health investment, occupational stress, and health shocks are more persistent than they appear to be in the full-sample analysis. We conclude that our estimates of the effects of occupational stressors are robust across specifications but that an analysis of the full sample leads to underestimation of the coefficient of lagged health. We may have underestimated the cumulative effects of occupational history by underestimating ϕ, and the predictions in the previous paragraph provide—in absolute terms—a lower bound on the health effects, which indicates that the true health effects may, in fact, be even larger.

Angrist and Pischke (2009) have voiced concerns about the violation of strict exogeneity in fixed effects dynamic models, particularly by utilizing short panels. They propose checking robustness by separately estimating both a fixed effects and a lagged dependent variable model. Column 3 of table 4 presents results from a fixed effects model without a lagged dependent variable. With respect to equation 9, the error term would now include the deviations of the effects of health investment, occupational stressors, and health shocks before period t-1 from their individual averages. If a past health shock would have a negative effect on current health and lead to higher occupational stress in the previous period, we would overestimate the effect of occupational stressors because this situation leads to additional correlation between $\mathbf{o}$ and the error term. The point estimates in column 3 suggest a somewhat stronger effect of manual handling of burdens and job control at older ages than the baseline specification. However, these estimates may be the result of a bias caused by past events that affected health and occupational choice that are not accounted for by the lagged dependent variable, which is omitted in this specification.

In a model in which we control for a lagged dependent variable, but not for individual-specific fixed effects, the estimator of the decay parameter ϕ in equation 9 is biased toward one because y_{t-1} contains h_p (see equation 7), which has a coefficient of one and no longer drops out if we do not subtract $\hbar y$. We can therefore no longer distinguish between the elements in y_{t-1} that are transitory and the elements that are constant over time, which explains the bias of the estimator of ϕ toward one. In this specification, we therefore overestimate the impact of past events on current health, and we only partly control for unobserved time-invariant heterogeneity. By not subtracting averages in equation 9, the error term now includes $(1-\phi)h_p$, which may be correlated with lagged health and occupational characteristics. To proxy for time-invariant unobserved factors otherwise picked up by the fixed effect, we control for years of schooling and gender. Our estimates are now mostly driven by variation among individuals. The coefficient of the interaction between age and manual handling of burdens is similar to our earlier results, but the coefficient of the interaction between age and job control is no longer significant. Workload now seems to have a positive effect; however, this result may ensue because we may be insufficiently controlling for the selection of healthy individuals into occupations characterized by high workload as a result of not controlling for individual-specific fixed effects. Overall, our main conclusions do not change when estimating models that include either individual-specific fixed effects or a lagged dependent variable, which is reassuring.

Other methods have been proposed to consistently estimate $\boldsymbol{\gamma_o}$ in equation 9 in short panels, of which the so-called Arellano-Bond estimator (Arellano and Bover, 1995; Blundell and Bond, 1998) is the most prominent. The Arellano-Bond estimator is based on the first-difference estimator. The most important assumption is that the second and further lags of health are uncorrelated with the first differences of the error term and can be used as instrumental variables for $h_{t-1} - h_{t-2}$. Unfortunately, the Arellano-Bond test for autocorrelation rejects this assumption in our case, which is not surprising because using lagged values as instruments is difficult to justify in the case of health: chronic illnesses or the introduction of a new medical drug may progressively affect health over time, which leads to second- or higher-order serial correlation in the differenced error term and violation of the exogeneity assumption. In attempting to overcome this problem, more lags of the regressors may be included in the model, and further lags of regressors and instruments may be used to purge the error term from autocorrelation. However, we still find higher-order autocorrelation in these models, rejecting the validity of the instruments.[8]

6 Conclusion

We find that both high physical occupational demands and low job control have negative effects on health. The immediate effect of (exposure to a one standard deviation increase in the degree of) handling heavy burdens (e.g., the shift from mail sorter to a bricklayer) during one year is comparable to aging five months. The immediate effect rises with age: if such a shift happens just before reaching retirement age, a similar increase in handling heavy burdens is comparable to aging 14 months. Low job control is equally harmful to health but only after age 36. After age 60, the immediate effect of low job control (e.g., shifting to being a nurse instead of a physiotherapist) is equivalent to aging 20 months. The estimated causal effect of carrying heavy burdens accounts for approximately 50 percent of the bivariate association between occupation and health, which implies that selection into occupation by prior health and/or other factors, such as education, accounts for the other half of the observed association.

Our empirical specification is derived from a theoretical model of occupation and health over the life cycle that reveals the conditions under which we can obtain causal estimates using a detailed longitudinal dataset over many time periods

[8]Limiting the number of waves can give us the false illusion that serial correlation of the error term is not a problem simply because of the low power of the test. Blundell and Bond and Michaud and Van Soest (2008) use short panels of six waves and "use up" even more waves due to the inclusion of lagged values of the dependent variable. The autocorrelation tests in these studies do not reject the assumption of no autocorrelation in the error term, which may be the result of limited test power based on the small number of waves. If we include one- and two-period lags of the dependent variable (Michaud and Van Soest (2008), we find no second-order autocorrelation. However, we find autocorrelation of the third-order, which still violates the Arellano-Bond assumptions. Including third or fourth lags seems to shift the order of autocorrelation downward rather than to solve the problem. The Sargan test may not be informative because it assumes that at least one instrument is exogenous, which is an assumption we are not willing to make.

(26 years). We argue that a fixed effects lagged dependent variable model neutralizes several time-invariant and time-varying sources of selection bias and is a valid identification strategy in the absence of exogenous variation in occupational stressors. Moreover, our results generalize across the entire labor force, which is in contrast to local effect estimates based on a particular reform that affected only part of the employed population. The coefficient of the lagged dependent variable should be interpreted as a decay parameter that captures the effects of past unobserved factors—which affected health in the previous period but could also have affected occupational choice—on current health.

We separate the health effects of physical and psychosocial stressors by linking German longitudinal data on occupational titles to Finnish data on occupational stressors. However, because we did not observe individual levels of health investment, we were unable to disentangle the effects of such occupational stressors and any health investment made in response to occupational choice. Our estimates should therefore be interpreted as the sum of the direct effect of occupation and the health effect of any behavioral response to occupational choice.

Occupational health and safety policies, career development programs, and retirement policies should be based on the knowledge that exposure to physically demanding manual handling of burdens and low job control is harmful to health at older ages. Shielding older workers from these conditions prevents health deterioration among vulnerable groups of workers and is likely to have a preventive effect against illness-related absenteeism and labor force exit due to disability.

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