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RISKS TO YOUNG PEOPLE AT WORK: EXPERIENCE OR EXPOSURE?

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ABSTRACT

Young workers in The Netherlands seem to have a relatively high frequency of occupational accidents. This paper sets out to examine to what extent this can be attributed to 1) their being young and inexperienced; in other words their human capital, and 2) selection of young workers into specific hazardous situations; in other words their exposure profile. The main contribution to the literature of this paper is an attempt to factor occupational safety into these two counterparts by means of an empirical model.

Results of the analysis could be helpful in defining a policy strategy. If the relative high accident frequency results from selection into hazardous situations, a regulation policy that keeps young workers away from these hazards or limits their exposure to these hazards, is called for. However, if the relative high accident frequency relates to human capital deficits, a policy of making young workers less vulnerable is the better option.

Based on an empirical model we conclude that high accident frequencies of young workers are not related to exposure. The high accident frequency is more likely the result of lack of experience, skills and training in handling risk. The model was estimated using data of a large survey, conducted in 2011, on the exposure to 64 occupational hazards and observed occupational accidents with and without injuries.

Crucial to the design of the model is the recognition of the fact that observing no accident for an individual worker in some period of time can come about in one of two ways. Either the worker is for that period of time 'invulnerable' and not exposed to hazards, rendering his risk to zero or the worker is vulnerable and exposed but he was not involved in accidents in the period of observation although he could have.

Furthermore a conceptual model is proposed to quantify exposure profiles using a limited number of variables.

1. INTRODUCTION

Young workers (15-24 years) seem to have a relatively high frequency of occupational accidents. Statistical analyses of labour force participation and accident frequencies indicate that young workers have a higher risk of occupational injury than older (over 25 years) workers. A wide variety of age related explanations has been put forward in the literature (EASHW, 2009), such as

- lack of
    - experience, skills and training
    - risk awareness (depending on rules instead of judgement)
    - knowledge (of appropriate safety measures to be provided and used)
    - maturity

- youngsters are less likely to speak out
- youngsters often work part time, with temporary contracts and are therefore less on-the-job-trained in handling risks.

This is why improving working conditions and skills of young workers are special focus points in EU safety and health policy.

In practice, protection of vulnerable groups, including young workers, is enforced by the employers' obligation to apply dedicated measures based on risks assessments. In addition, some restrictions apply for workers under 18, limiting their exposure to certain hazards. However, in a recent study the European Agency for Safety and Health at Work (EASHW, 2009) suggests that extra measures are needed. In general, strategies to protect young workers can be divided in two: 1) making them less vulnerable; and 2) keeping them away from occupational hazards.

Making young workers less vulnerable is a human capital approach: individual safety results from people acting differently given the same working conditions. That is, one individual might be more skilled, aware, experienced or trained to increase his safety than another while the exposure to hazards is the same for both. This approach has a clear advantage: wherever the more skilled individual goes, he brings this specific human capital with him. His skills are applicable in many situations.

In the second approach safety results from changing the circumstances for a group of individuals. Accidents are avoided by improving working conditions and lowering exposure thereby lowering their risk. In essence, the question is to which approach should policy adhere to? This paper sets out to separate circumstances from individual characteristics by means of a statistical modelling of data collected for the ORCA-project of the Dutch National Institute for Public Health and the Environment (RIVM).

ORCA (Occupational Risk Calculator)[1] is a software tool for companies and workers that calculates occupational risk and suggests the most cost-effective set of measures available to reduce this risk. The tool contains objective quantitative accident and exposure data in order to lay the foundation for risk-oriented policymaking on occupational safety. ORCA is based on the self-reported exposures to occupational hazards and working condition qualities.

To keel ORCA up to date, exposure to hazards data of 25 thousand respondents were collected using a survey in 2011 (RIVM, 2012). In addition, 23 thousand serious accidents investigated by the Dutch Labour Inspectorate in 1998-2009 were analysed (Bellamy, 2008). At the heart of ORCA 64 occupational hazard models are quantified resulting in a risk rate: the probability of having a serious accident per hour exposure (RIVM, 2008). The present paper is based on ORCA-data. The data are described in more detail in chapter 3.

The relative high accident rate of young workers in the Netherlands can be illustrated by simple statistics. Their share in serious occupational accidents is estimated at 22 per cent, whereas their share in the total amount of time exposed to 64 hazards is only 15 per cent (RIVM, 2012). So on average, their accident frequency is roughly a factor 1.5 higher. However, on the level of specific hazards this is not always the case .Young workers turn out to have a relatively low accident frequency when working on heights: that is working on ladders, working on fixed scaffolds, working near holes in the ground, using cherry pickers, using stairs etc. Young workers also have a relatively low accident frequency when physical strength, agility and fitness are involved. On the other hand, their accident frequency is high when exposed to all occupational hazards involving operating, maintaining or cleaning fixed machines or working with hand tools. This means that the vulnerability of young workers is heterogeneous: it varies with the circumstances and the related hazards. Therefore, we will analyse the occupational accident frequency of workers by means of an empirical model that allows controlling for individual characteristics (such as age, gender, sector) and the personal exposure profile.

The paper proceeds as follows. In Section 2 an analytical framework is presented. Data are described in Section 3. Section 4 presents empirical results, Section 5 concludes.

2. ANALYTICAL FRAMEWORK

In this section an analytical framework is introduced to explore the relationship between occupational risk, exposure to hazards and background variables such as age, gender, profession and industrial sector.

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[1] www.weborca.nl

2.1 Empirical model

The proposed empirical model is a regression model. It relates an outcome Y of interest to a set of explanatory variables X. Variables Y and X are observed for a sample of individuals. The main goal of the regression is to find out to what extent Y and X co-vary when all X-variables are taken into account simultaneously. In the present analysis the outcome Y is defined as the number non-fatal occupational accidents (of any type) observed for an individual worker in the past 12 months. Since Y is a non-negative integer count with an excess amount of zero-observations the 'standard' ordinary least squares regression model is not suitable.

The literature offers a wide variety of count data models to regress such a variable on a set of independent variables (see for example Cameron and Trivedi, 1998). A well-known example is the Poisson model. The applicability of this model however is limited due to the fact that it imposes equi-dispersion, which means that the conditional mean and variance are equal. This is a rather strong assumption that is hardly ever met in practice. A more flexible count data model is obtained when unobserved heterogeneity is introduced in the Poisson intensity parameter λ. The most commonly used extension to the Poisson model is the negative binomial model (NEGBIN), which results when λ is mixed with a gamma distribution. The NEGBIN model imposes over-dispersion, meaning that the conditional variance exceeds the mean. The model contains the Poisson model as a directly testable special case.

In this study the individual count of occupational accidents is regressed on observed independent variables by means of the negative binomial model. However, data on occupational accidents usually display a higher number of zero-observations than can be accounted for by the assumed density. To accommodate this fact the model is extended with a special treatment of the zeros. In other words, the zero observation – that is no accident suffered in the year of observation - is assumed to be the result of two independent underlying processes. The first process determines whether an individual was in the position of being involved in an occupational accident. We refer to this as the individual being 'vulnerable to accidents'. This is a binary process that can be modeled by means of a standard logit or probit model. It should be stressed that this binary process is not observed. We do not actually observe a discrete indicator which divides our sample in people who are vulnerable to accidents and people who are not. The model will only predict the *probability* that an individual is vulnerable to occupational accidents conditional on characteristics that are supposed to relate to this vulnerability.

The second process is a count of accidents described by the negative binomial model, conditional on the (latent) outcome of the first process. Now zero observations can come about in two ways: a) either the individual was invulnerable and not exposed to hazards; or b) the individual was vulnerable but was not involved in an occupational accident in the year of observation. This way of modeling zero observations is typical for the zero-inflated negative binomial model (ZINB). The model is written as

$$\Pr(Y_i = y_i) = \begin{cases} \pi_i + (1-\pi_i)(1+\rho\lambda_i)^{-\rho^{-1}} & \text{if } y_i = 0 \\ (1-\pi_i)\frac{\Gamma(\rho^{-1}+y_i)}{\Gamma(\rho^{-1})\Gamma(y_i!)}\left(\frac{\rho\lambda_i}{1+\rho\lambda_i}\right)^{y_i}(1+\rho\lambda_i)^{-\rho^{-1}} & \text{if } y_i > 0 \end{cases} \quad (1)$$

In the above equation Y_i is the count of non-fatal occupational accidents in the year of observation and y_i the observed realization of this count for individual i. The parameters of interest are π_i and λ_i, where 1-π_i is the probability that individual i is vulnerable to accidents and λ_i is the incidence rate of accidents happening to the vulnerable individual. To both the subscript i is attached to stress the fact that they are parameterised to reflect individual heterogeneity. The non-negative parameter ρ captures the degree of over-dispersion. If it converges to zero, the model reduces to the zero-inflated Poisson model (ZIP). The expected number of occupational accidents individual i suffers in one year is equal to the product of the probability of being accident-vulnerable and the incidence rate, that is

$$E(Y_i) = (1-\pi_i)\lambda_i \quad (2)$$

where π_i and λ_i, are functions of individual characteristics such as gender, age, profession, sector, exposure etc. For the count part of the model we use the NEGBIN I model, which is parameterised such that ρ is scaled by λ_i. This means that ρ varies across individuals and that – conditional on covariates - the count variance is a linear function of the count mean. The π_i-part of the model is estimated by a probit model. The model is estimated by using the zinb-procedure in STATA.

2.2 Model specification and identification strategy

The essence of the ZINB-model is the recognition of the fact that the zero-accidents observation can be the result of two different underlying processes. On the one hand, people may somehow not be vulnerable to occupational accidents. This results in a zero-accidents observation that is reflected by the first term in the upper part of equation (1) . On the other hand, a zero-accidents observation arises when a worker is vulnerable but at the same time lucky enough not to get involved in accidents in the period of observation (second term in the upper part of eq 1).

The present empirical analysis focusses on the attribution of occupational safety to two aspects: 1) the likelihood of being vulnerable to accidents; and 2) the incidence rate of accidents when vulnerable. In the specification of π_i personal characteristics such as age, gender and sector are concentrated. The accident incidence rate λ_i reflects individual differences in exposure to hazards. Incorporating variables of interest in both parts of the model is in our view bad practice, since the identification of partial effects would be based on assumptions with respect to functional form only. We refrain from this and assign each and every covariate to just one part of the model. Assignment is based on the hypothesis that the incidence rate should be proportional to exposure rather than that it is driven by personal characteristics. In other words, we assume in our specification that an accident occurs with a frequency irrespective of individual characteristics, it occurs proportional to exposure conditions. Persons do not differ in the incidence rate of accidents happening to them conditional on exposure. Of course this is a simplified representation of reality. Because individual characteristics as attitudes but also strength, eyesight and other senses, height et cetera can make a difference. As a consequence such aspects are implicitly enclosed in the probit part of the model, that represents the accident-vulnerability of the individual. We will further elaborate on this issue at the end of this section.

We will use the model to assess occupational risk of groups of individuals by calculating the yearly expected number of accidents by inserting the estimated parameters of the model (hereunder depicted with ^) in equation (2).

$$Occupational\ risk = (1-\hat{\pi}_i)\hat{\lambda}_i \qquad (3)$$

In equation (3) the first term on the right hand side – ($1-\pi_i$) – is the individual's occupational risk arising from being vulnerable to occupational accidents. In our specification of the model this is the particular selection of individuals including their labour market choices with respect to for instance working hours, job preference etc. The second term is the risk attributed to the individual's exposure to hazards. The model allows us to assess how occupational risk breaks down into two components: 1) the probability of being vulnerable to occupational accidents; and 2) to what extent the risk is exposure driven. Although from a policy perspective minimising the total risk should be the objective, we argue that the relative size of both components can tell which policy strategy to adhere to: *a)* by training particular groups of individuals to reduce their vulnerability (*human capital approach*, (Becker, 1964)) or *b)* reducing exposure to specific hazards (*regulation approach*). A relatively high first component may call for the human capital approach, whereas a high second component may give rise to the regulation approach.

As noted earlier, the assignment of covariates to the different parts of the model is the model builder's choice rather than an empirical outcome. The chosen model specification relies on the assumption that intensity of exposure to hazards has a stronger impact on the incidence rate than personal characteristics. We will test this assumption by splitting observed variation on the intensive and extensive margin of accidents in an alternative way. First a probit model – specified as in the probit part of the ZINB-model – is fitted on a dummy transformation of Y_i. An alternative estimate for λ_i is calculated by setting the upper part of equation (1) equal to the prediction of the probit model and solving for λ_i given the ZINB-estimates for π_i and ρ. Note that the probit model does not take into account the variation above one accident per year (the intensive margin); it solely exploits the individual variation of having been involved in an accident or not (the extensive margin). Now if the ZINB-estimate of λ_i highly correlates with the alternative estimate and does not alter when personal covariates are added, this indicates that the ZINB-estimate of λ_i mainly reflects heterogeneity on the intensive margin of accidents, which it is supposed to. Results of this test are presented in Section 4.4.

2.3 Exposure profiles

In our survey the exposure to 64 different occupational hazards is observed. Of every hazard the yearly exposure is estimated using the reported exposure in an average week. Exposure profiles may vary in many ways. Some workers are exposed to only few hazards, others to many hazards. Some are exposed for long time spans, others for short intervals. And within the individual set of hazards, exposure duration may vary. In order to bring down the number of possible exposure profiles, we define three basic dimensions:

1. the number of hazards exposed to (N_i);
2. the total exposure time (T_i);
3. the exposure variety (V_i).

In Figure 1 the worker population is divided into four main profiles by first dissecting at the median number of hazards along the vertical axis. The median equals 4 hazards. The two remaining populations are both cut in half at the medians of the total exposure duration (1135 hours/year for the left hand side and 3260 hours/year for the right hand side in Figure 1). The remaining four profiles are each divided into two equal subsets by the inner circle marking the hazard variety. The degree of variety is assessed by means of the Blau diversity index (Blau, 1977). The subsets closest to the origin reflect risk profiles with low variety. Again, the median of the index within each profile is used to cut the worker population in halves. We end up with eight profiles numbered counter clockwise 1 through 8 in Figure 1. In essence, the total worker population is now separated into 8 equal parts containing 12,5% of the total worker population. We may exploit the exposure profiles to describe to what extent various subpopulations such as males, females, young workers deviate from 12,5%.

Figure 1. Eight exposure profiles

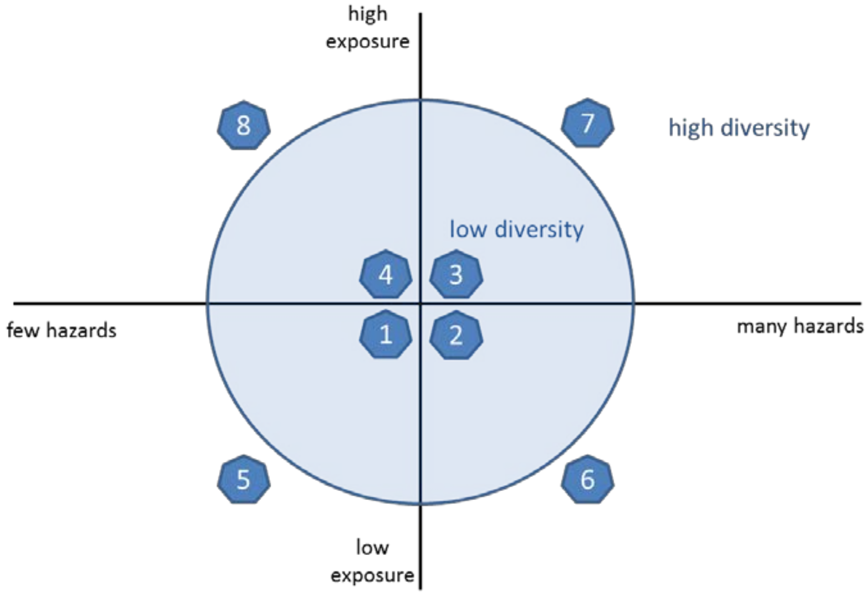


Table 1 Exposure profiles: average number of hazards and (cumulative) exposure duration

Profile	Hazards	Exposure (hrs/yr)	Profile	Hazards	Exposure (hrs/yr)
1	2.0	574	5	2.7	577
2	6.4	1648	6	8.6	2353
3	8.6	4818	7	16.9	11523
4	2.4	1494	8	3.2	2370

Table 1 displays descriptive exposure statistics for the profiles. As can be seen, profiles 1 and 5 (left bottom quadrant in Figure 1) differ only marginally, whereas profiles 3 and 7 (right upper quadrant) differ markedly in the number of hazards as well as total exposure duration. The total average of hazards exposed to equals 5.7, with a total exposure duration of 3170 hours per year. Note that one year consists of roughly 1600 working hours.

3. DATA DESCRIPTION

The data were originally collected in order to quantify the occupational risk model ORCA (Papazoglou, 2008). In 2009/2010 the ORCA tool and data were evaluated by a team of occupational safety experts. One of their recommendations was to update the exposure data on a regular basis, resulting in a follow-up survey

Exposure to Occupational Hazards (in Dutch: Enquete Blootstelling aan Arbeidsgevaren 2011, abbreviated as EBA 2011). The data of this follow-up survey were used in this paper.

The data collection for EBA 2011was conducted in the spring of 2011. The Internet panel used, contained over 125,000 respondents, of which about 70,000 constitute a representative sample of the Dutch working population, having a job (steady, flexible, self-employed) and falling into the age categories 15 – 65 years. To obtain a comparable sample size (30,000 in 2006) over 48,000 members were invited to participate in the research. Over 30,000 members responded on the invitation and returned the survey, after data cleaning the dataset contained over 25,000 cases.

In the survey exposure was assessed by taking a snapshot of all exposures in one typical working week. Respondents reported their exposure to 64 hazards during one specified week. By focussing on just one recent week, the survey does not draw heavily on the respondent's memory. It is unlikely that people can recall the exact exposure spells over a year or even a month. Seasonal variance in exposure cannot be identified in the data.

To obtain exposure data representative for the Dutch working population, weights were calculated to conform with known marginal distributions .The weighting was done by applying an iterative procedure in which the cell frequencies were estimated, given the distributions of the variables: gender, age, education level and hours per workweek, type of employment and industry sector. This way of weighting was necessary because a total distribution for all variables was not available and post-stratification was not possible due to empty cells.

The EBA also collected information on occupational accidents. Resulting in a data file combining accidents and exposures. Factoring up for The Netherlands 210,000 accidents with at least one day of absence were self-reported by EBA respondents. This is close to the total number of occupational accidents estimated by TNO: 224,000 (TNO, 2012). We conclude from this that EBA does not suffer from underreporting of accidents more than other surveys.

4. RESULTS

4.1 Model estimation results

In Table 2 estimation results are presented. The individual exposure to 8 main hazard categories is exploited to estimate the incidence rate of occupational accidents. For scaling purposes exposure is measured in full time equivalents. Five out of eight hazard categories show significant positive coefficients: slips & trips and falling from heights, being hit by moving objects, dealing with animals and humans, working with extreme temperatures and danger of suffocation/being in confined space. For the remaining three hazards the incidence rate of accidents is not affected by the duration of the exposure. The coefficient 0.51 for exposure to slips & trips and falling means that the expected number of occupational accidents increases by a factor $e^{0.51} \approx 1.66$ if exposure increases from zero to full time exposure, holding everything else constant. In other words, a 66 per cent increase for full time exposure, a 33 per cent increase for half time exposure etc. Remarkably, the incidence rate shows a sensitive response to exposure to dealing with (aggression of) living creatures. The expected number of accidents increases by a factor $e^{1.39} \approx 4$. In other words, the occupational risk quadruples if exposure increases from zero to full time exposure, and doubles for half time exposure.

The bottom part of Table 2 presents the coefficients of covariates in the probit component of the model expressing the probability of being vulnerable to accidents. Significant positive effects are observed for age, high educational level (compared to low level), temporary workers (compared to wage workers with a fixed contract), the weekly hours and the sectors retail and business services (compared to the public sector). A positive effect indicates a lower probability of being accident-vulnerable. Marginal effects are hard to assess at face value, since they are multiplied by the Gaussian density function. We will discuss average marginal effects in terms of per cent points of the probability of being accident-vulnerable.

The estimation results show that as workers become less vulnerable to accidents as they grow older. One might hypothesise this could be due to accruing human capital: workers may become more experienced in recognizing potential dangers as time goes on. On average a one year increase in age decreases the probability of being accident-vulnerable by 0.7 per cent points. So, every 10 years of working experience decreases vulnerability by 7 per cent points. Workers with a high level of education have on average a 17 per cent point lower vulnerability than workers with a low educational level. For temporary workers vulnerability is 20 per cent point lower. Furthermore, the estimation results show a positive effect of the variable 'part time factor'. This variable measures the relative job size compared to a full time 40 hours a week jobs. The positive sign means that vulnerability decreases with job (contract hours) size. A full time worker has a 9 per cent point lower vulnerability than the same worker in a 20 hours job (with equal absolute hazard exposure). Again this could be a human capital effect. Full time workers get more training-on-the-job in being aware and recognising danger, even when they are not actually exposed.

Negative effects are reported for the sectors health care and education. This implicates that all else held constant health care workers and teachers are more vulnerable to accidents than civil servants (the reference sector). The significant dispersion parameter indicates that the count of accidents is over-dispersed; the negative binomial distribution fits the data better than the Poisson distribution would.

Table 2 Estimation results: zero-inflated negative binomial count model of occupational accidents

	Estimate	Std. Error	T value
Incidence rate λ			
Constant	-2.74***	0.27	-10.19
Hazard exposure (in fte's)			
- slips and trips and falling	0.51**	0.20	2.50
- moving objects	0.94***	0.24	3.95
- aggressive animals and humans	1.39***	0.16	8.66
- machines and vehicles	-0.12	0.15	-0.77
- electricity/high voltage	-0.19	0.14	-1.37
- extreme temperatures	0.81*	0.48	1.68
- chemicals and explosions	-0.17	0.28	-0.59
- suffocation/confined space	0.65**	0.31	2.14
π = Pr(individual is not accident-vulnerable)			
Constant[†]	-1.64**	0.67	-2.47
Age	0.02***	0.01	3.58
Female	-0.17	0.17	-1.00
Intermediate level of educational	0.11	0.17	0.61
High level of education	0.55**	0.21	2.56
Temporary wage workers	0.67*	0.40	1.67
Self-employed workers	-0.07	0.20	-0.36
Part time factor	0.58*	0.34	1.71
Industry	0.08	0.22	0.39
Construction	-0.46	0.40	-1.17
Retail	0.32*	0.18	1.74
Transport	-0.65	0.43	-1.50
Business services	0.41**	0.18	2.32
Education	-0.45*	0.27	-1.65
Health care	-1.33*	0.76	-1.74
Other sectors	-0.21	0.25	-0.83
Dispersion parameter ρ	1.61	0.20	8.14
Observations	Zero	Non-zero	
	23083	1305	
Average accident count non-zero observations	1.55		
Number of iterations	8		

[†] constant refers to male workers in public sector with low level of education and zero age

*** significance level >99%; ** significance level 95-99%; * significance level 90-95%

4.2 Occupational risk of worker subpopulations

Individual occupational risk is assessed according to eq (3). Occupational risk (OR) is defined as the expected number of accidents (including the less serious incidents without absence) in one year. It breaks down into two components: accident-vulnerability (AV) and exposure (E). Table 3 shows averages of occupational risk and both components for several worker subpopulations. From Table 3 we conclude that average occupational risk is estimated 0.10, meaning that the average expected number of accidents (including those without absence of work) in year equals 0.10. The components amount to 0.61 and 0.15 respectively, which means that the average probability of being accident-vulnerable is 61 per cent and the hazard exposure profile contributes for on average 15 per cent.

As can be seen in Table 3, in general young workers show higher occupational risk than workers older than 25: 0.13 and 0.09 respectively. Young workers turn out to have a much higher vulnerability (71 per cent compared to 59 per cent), whereas their hazard exposure is only marginally higher (0.17 compared to 0.16). From this we conclude that occupational safety of young workers - and especially of young women (see below) - may be most effectively enhanced by focusing policy on accumulation of human capital (training in risk awareness, making young workers less vulnerable) rather than on decreasing their exposure to hazards by regulation.

On average males and females show similar occupational risk (0.10), but it breaks down differently. Men tend to have higher exposure to hazards than women (0.17 and 0.14 respectively), but the latter are more vulnerable to accidents (0.70 compared to 0.53). A remarkable result in Table 3 is the relative low occupational risk of temporary workers. On the basis of their temporal relation to employers, a potentially higher occupational risk may be expected. This is however contradicted by the model estimations. Temporary worker have lower occupational risk, mainly due to low exposure.

Table 3 Occupation risk (OR), accident proneness (P) and exposure (E) of worker subpopulations

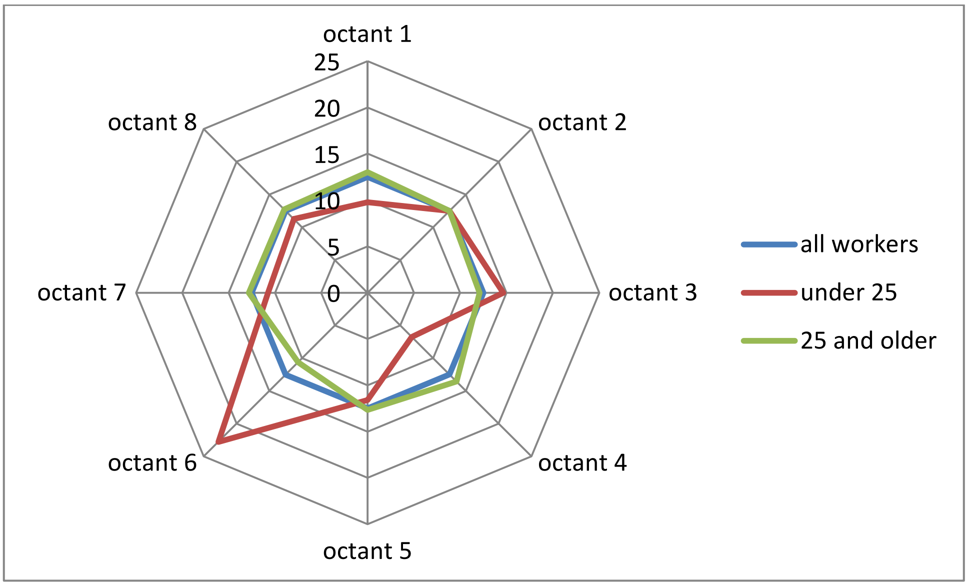
	All ages			Under 25			25 and older		
	OR	AV	E	OR	AV	E	OR	AV	E
all workers	0.10	0.61	0.16	0.13	0.71	0.17	0.09	0.59	0.16
males	0.10	0.53	0.17	0.12	0.65	0.18	0.09	0.51	0.17
females	0.10	0.70	0.14	0.13	0.76	0.17	0.10	0.68	0.14
wage workers, fixed contract	0.10	0.62	0.16	0.16	0.75	0.20	0.10	0.60	0.16
temporary workers	0.07	0.58	0.13	0.09	0.63	0.14	0.06	0.52	0.12
self employed	0.08	0.52	0.16	0.12	0.79	0.16	0.08	0.51	0.16
full time	0.09	0.50	0.17	0.11	0.64	0.17	0.09	0.48	0.17
big part time	0.12	0.61	0.18	0.19	0.75	0.25	0.11	0.59	0.17
small part time	0.09	0.71	0.12	0.09	0.72	0.13	0.08	0.70	0.12
Industry	0.09	0.49	0.17	0.11	0.63	0.18	0.08	0.48	0.17
Construction	0.12	0.71	0.17	0.15	0.79	0.19	0.12	0.70	0.17
Retail	0.10	0.48	0.20	0.10	0.58	0.17	0.10	0.46	0.21
Transport	0.12	0.76	0.16	0.12	0.85	0.14	0.12	0.75	0.16
Business services	0.04	0.37	0.10	0.07	0.50	0.13	0.04	0.35	0.10
Public sector	0.06	0.49	0.12	0.08	0.64	0.12	0.06	0.48	0.12
Education	0.10	0.67	0.15	0.14	0.76	0.19	0.09	0.65	0.15
Health care	0.15	0.93	0.17	0.20	0.96	0.21	0.14	0.93	0.16
Other sectors	0.12	0.64	0.19	0.13	0.72	0.18	0.12	0.61	0.19

4.3 Exposure profiles

In Table 4 the occupational risk of eight exposure profiles defined in Figure 1 is presented. The profiles in octants 3 and 7 display the highest occupational risk, due to high and sometimes divers exposure to many hazards. Young workers turn out to be overrepresented in octants 3 and 6 of which the latter does not add to their high risk. The relatively large number of young workers in exposure profile 3 in combination with small numbers in the low-risk profiles 1 and 4 is the main reason why they face higher occupational risk. Their high risk in profile 3 is driven mainly by vulnerability. Keeping young workers away from working conditions in which they are highly exposed to many hazards simultaneously could be effective policy to enhance the overall occupational safety of this specific group.

Table 4 Occupation risk (OR), accident proneness (P) and exposure (E) in 8 exposure profiles

	All ages				Under 25				25 and older			
	OR	AV	E	%	OR	AV	E	Δ%	OR	AV	E	Δ%
Octant 1	0.04	0.57	0.07	*12.5*	0.05	0.67	0.07	*-2.8*	0.04	0.56	0.07	*0.5*
Octant 2	0.07	0.63	0.10	*12.5*	0.08	0.71	0.11	*0.0*	0.06	0.62	0.10	*0.0*
Octant 3	0.19	0.62	0.30	*12.5*	0.24	0.74	0.31	*2.2*	0.18	0.59	0.30	*-0.4*
Octant 4	0.04	0.51	0.07	*12.5*	0.06	0.67	0.08	*-5.8*	0.04	0.49	0.07	*1.1*
Octant 5	0.05	0.60	0.08	*12.5*	0.05	0.69	0.08	*-0.9*	0.05	0.59	0.08	*0.2*
Octant 6	0.09	0.67	0.13	*12.5*	0.09	0.70	0.13	*10.3*	0.09	0.66	0.13	*-1.9*
Octant 7	0.22	0.61	0.36	*12.5*	0.30	0.72	0.41	*-1.8*	0.21	0.59	0.35	*0.3*
Octant 8	0.10	0.62	0.15	*12.5*	0.13	0.75	0.17	*-1.3*	0.09	0.60	0.15	*0.2*



4.4 Testing specification assumptions

In Table 5 the model specification assumption is visually tested. The ZINB-estimate of λ_i is regressed on the alternative estimate using a simple prediction of the probability of zero accidents and the ZINB-estimates for π_i and ρ. If the ZINB-model perfectly describes the accident generating process and all relevant covariates were included in the correct part of the model, we should observe a fairly constant estimate for the alternative λ_i as more control variables are gradually added to the OLS-regression. The R^2 should also be constant and close to unity.

Table 5 Assumption test: OLS regression of log incidence rate λ_i on alternative estimate of log λ_i

	(1)	(2)	(3)	(4)
Alternative log λ_i	0.68	0.67	0.67	0.66
Standard error	0.00	0.00	0.00	0.00
Control variables				
- Age, gender, education	No	Yes	Yes	Yes
- Labour market: sector, contract type, part time	No	No	Yes	Yes
- Sector dummies	No	No	No	Yes
Adjusted R^2	0.85	0.86	0.87	0.88

Table 4 shows that 85-88 per cent of the variation in λ_i can be accounted for by the alternative estimate. Incorporation of control variables leads to just a slight increase of the adjusted R^2. The estimated coefficient slightly drops from 0.68 to 0.66. From this we conclude that the absence of personal characteristics in the incidence rate is based on the fair assumption that on average the exposure to hazards has a stronger impact on the incidence rate than personal characteristics. This follows from the fact that a simple prediction of the ZINB-estimation of λ_i based on limited accident information is not seriously affected the inclusion of personal characteristics. Apparently the ZINB-estimate of λ_i hinges strongly on variation in the observed number of accidents conditional on individual exposure.

5. CONCLUSION

Young workers are considered to be more at risk of having an occupational accident. Exposure and accident data collected for the development of an quantified occupational risk model shows that young workers indeed have a considerable higher risk but not for each and every hazard and different exposure profiles have different effects on the chance of having an accident.

To reduce the risk of young workers of being involved in an occupational accident the European Agency for Safety and Health at Work (EASHW) suggests two lines of defence:
1) make young workers less vulnerable;
2) protect young workers from exposure to occupational hazards.

Based on our empirical model explaining the occurrence of accidents in relation to age and other background variables on the one hand and exposure profiles on the other, we conclude that policy 1 is to be preferred (that is: offers most room for improvement) and especially for young women. Policy 2 can be considered in situations where young workers are exposed to many hazards simultaneously. That is: reducing the number of hazards, not necessarily the duration of the exposure.

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