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A PRODUCTION COMPANY SIZE AND WORKPLACE SAFETY HAZARDS

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Purpose: The objective of the study is to examine whether a wood processing company size affects the differentiation of workplace safety hazards as well as to investigate the influence of features characterizing an occupational accident casualty on their injury severity, considering the company size.

Methodology: The study used non-aggregated data obtained from the Central Statistical Office, Poland. The data for analyzes were prepared through quality diagnosis, cleaning and transformation. Variables of no informative value were excluded from further investigation. Statistical tests were performed implicating the need for independent analyzes for two data subsets referring to: micro and small enterprises (employing up to 49 persons), and medium and large enterprises (employing 50 persons or more). For each of the two company groups, a logistic model was developed classifying the occupational accident casualty injury severity based on the casualty characteristics. In each case, the classification quality was assessed using a test data set.

Findings: It was shown that the enterprise size had an impact on the severity of accidents at work and that the proposed method of classifying enterprises by size into two categories was justified. Explanatory variables in logistic models were interpreted according to their importance and intensity of influence on the explained variable.

Practical implications: The obtained results can be used in the development of materials on occupational safety risks for entrepreneurs and OSH services.

Social implications: Each type of economic activity carries various risks. Occupational accidents pose a serious social and economic problem. Research in the field of occupational safety allows a better understanding of the nature of such accidents and makes it possible to take effective preventive actions which, however, can depend on a company size.

Originality/value: On the basis of the obtained results, it is possible to identify the factors influencing the severity of occupational accidents in wood processing companies according to their size. The research also showed that bivariate multiple logistic regression is an appropriate tool for analyzing occupational accident data.

Keywords: occupational accident casualties; production company size; tests for equality of proportions; logistic models.

Category of the paper: Research paper.

1. Introduction

Each type of economic activity carries various risks. Occupational accidents pose a serious social and economic problem. Research in the field of occupational safety allows a better understanding of the nature of such accidents and makes it possible to take effective preventive actions. The study focuses on work safety problems in Poland; selected aspects of accident phenomenon research were analyzed. Data analysis methods such as statistical tests, data balancing, and logistic regression were used for a specified manufacturing sector – wood processing.

Statistical modeling and data-mining techniques are popular methods in occupational accident-related studies (Chan et al., 2022). The most common are: artificial neural networks (e.g. Ayhan, Tokdemir, 2020), association analysis (Martínez-Rojas et al., 2022), Bayesian networks (Lu et al., 2020), cluster analysis (Nowakowska, Pajęcki, 2021), decision trees (Martínez-Rojas et al., 2020), linear regression (Nowobilski, Hoła, 2022), logistic regression (Hansen et al., 2022), support vector machines (Mangeli et al., 2019), text mining (Shi, Rothrock, 2022).

Logistic regression (LR) allows introducing both qualitative and quantitative explanatory variables into the model equation and has the capability of estimating and quantifying meaningful results in terms of odds ratios. LR analysis, in particular binary LR, has been widely used in studies related to occupational safety to classify occupational injuries and extract information to improve workplace safety. Among work safety analysis studies, the explained variable does not always refer to the degree of injury of the accident casualty – it is defined in different ways, depending on the purpose of the research. One can find the regression modeling regarding occupational safety and health (OSH) in various areas of the economy, such as agribusiness or agricultural industries (Hayati et al., 2021; Davoudi Kakhki et al., 2019; Swanton et al., 2016), electrical industries (Gholizadeh, Esmaeili, 2020), mining (Yedla et al., 2020; Onder, Mutlu, 2017), metal industry (Durmaz, Atalay, 2021; Kifle et al., 2014), construction (Halabi et al., 2022; Dong et al., 2020), petroleum manufacturing (Tsai et al., 2011), or automotive manufacturing (Reyes et al., 2015). However, its use in occupational safety analysis as regards the woodworking industry has been minimal.

Dida et al. (2019), in their study, focused on workers from small-scale industries in Southeast Ethiopia, including woodwork. They modeled occupational injury using binary (dichotomous) simple and multiple logistic regression. The following conclusions were drawn: (1) workers who took health and safety training involving their profession were less likely to be injured compared to those who did not take the training, (2) lack of supervision, any objects on the floor that can cause an accident, and low occupational risk perception increased the odds of occupational injury by several times in comparison to the respective opposite work circumstances. Bentum et al. (2021) discussed occupational safety conditions in wood and wood products processing industry in a selected region of Ghana (in relation to informal woodworkers). The authors examined the influence of socio-demographic variables on the usage of PPE (personal protective equipment, a binary explained variable). Any educational level (as referenced to illiterate) and over 10-year service of the woodworkers positively influenced their PPE usage. Among four job types, only machine operators had strong positive attitudes to protect themselves against occupational injuries and death.

Various industry sectors are considered to be dangerous in terms of OSH, depending on work conditions in a country, a sector, or a company, and workplace safety climate, including the production company size. The most frequently indicated ones are construction and mining. In Poland, in addition to the industries mentioned above, the occupations in wood processing are rated with high accidents and injuries (Pajęcki, 2020). Wood industry workers are highly susceptible to injuries and accidents due to the hazardous and risky nature of their work connected with the performance of many dangerous operations occurring in the production process, such as cutting, planning, sawing, other mechanical processing, gluing and laminating.

The objective of the study is to examine whether a wood processing company size affects the differentiation of workplace safety hazards as well as to investigate the influence of the features characterizing an occupational accident casualty on their injury severity, considering the company size.

The paper is organized as follows. After this background section regarding the modeling of occupational accident circumstances in various industry sections, including woodworking, the methodology section details are presented. Then, data preparation for logistics modeling is described. Next, the results of the modeling process are demonstrated for the companies of two categories as regards the company size, and the hazardous accident tendencies observed in this trade are outlined. Finally, the findings of the study are discussed and summarized.

2. The methodology approach

Bivariate multiple logistic regression is a classifier used to identify the relationship between the explanatory variables and the explained variable (Agresti, 2013). The explained variable takes two values; one is usually called a success or an event and the other is called a failure or a non-event. The logistic classifier estimates the probability of the explained variable Y taking the category of the success at certain values of the explanatory variables X_1, ..., X_k, according to the formula:

$$P(Y = Success \mid X_1 = x_1, \dots, X_k = x_k) = \frac{\exp(B_0 + \sum_{i=1}^{k} B_i \cdot x_i)}{1 + \exp(B_0 + \sum_{i=1}^{k} B_i \cdot x_i)} \quad (1)$$

In the study, *Casualty injury severity* is the explained variable and it is considered as a risk-related OSH measure. The variable takes two values: *Serious* (success, event) and *Other* (failure, non-event).

The odds and the odds ratio are utilized in logistic regression. The odds are defined as the quotient of the probability of success and the probability of failure. The odds can be determined for two groups of observations, which differ in the value of a specific explanatory variable. The quotient of these ratios defines the odds ratio *OR*. *OR* allows the interpretation of the logistic regression structural parameters; the possibility of success in one group is compared to the success in the other group. When X_i is a qualitative variable, the *OR* informs that the odds of the explained variable taking the success value are for the $k2$ category of the explanatory variable X_i as $\exp(B_i)$ of the odds for the $k1$ reference category of that variable, with the other inputs fixed (ceteris paribus):

$$OR\left(X_{i,\ (k2\ vs\ k1)}\right) = \frac{P(Y = Success \mid X_i = k2)\ /\ P(Y = Failure \mid X_i = k2)}{P(Y = Success \mid X_i = k1)\ /\ P(Y = Failure \mid X_i = k1)} = \exp(B_i) \quad (2)$$

An odds ratio is always non-negative and it matters in the logistic model if the parameter that defines it is statistically significant. An odds ratio of 1 indicates no influence. An odds ratio greater than 1 indicates that the specific factor increases the odds of the success (a positive influence), while an odds ratio less than 1 indicates that the factor decreases the odds of the success (negative influence). The further the *OR* value is away from unity, the stronger the influence, positive or negative, of the factor on the explained variable is.

The following tools were used to assess the obtained logistics models (Hand et al., 2001; Agresti, 2013):

- Model Significance Likelihood Ratio Chi-Square test.
- The *AIC* and *SBC* measures.
- Classification quality measures:
  - Sensitivity, True Positive Rate (*TPR*; *Serious* → *Serious*): $TPR = \frac{TP}{TP+FN}$.
  - Specificity, True Negative Rate (*TNR*; *Other* → *Other*): $TNR = \frac{TN}{TN+FP}$.
  - Proportion Correctly Classified (*PCC*): $PCC = \frac{TP+TN}{TP+TN+FP+FN}$.
  - Harmonic Mean Of Sensitivity And Specificity: $HMSS = 2 \cdot \frac{TPR \cdot TNR}{TPR+TNR}$.

Sensitivity measures the proportion of correctly classified successes (serious casualty injury severity), whereas specificity measures the proportion of correctly classified failures (other casualty injury severity).

The model estimation process was carried out in several steps, as described below.

1. The raw data set was partitioned into training and test data sets, in the proportions: 70% to 30%.
2. In order to compensate for the negative impact of the unequal distribution of the explained variable on the modeling results, a balanced set (50% of successes, 50% of

failures) was created from the training data set (Hand et al., 2001), on the basis of which the logistic regression model was built.

3. Stepwise selection of the explanatory variables was applied in the logistic model estimation process.
4. Classification quality was assessed on the test data set and the unbalanced training set.

SAS Enterprise Miner was used in the calculations.

3. Data preparation for logistics modeling

Data for the analysis were acquired from the occupational accident database of the Central Statistical Office (CSO), Poland. The Office conducts tasks in the scope of recording and managing all occupational accidents data in the whole country. The data structure reflects the structure of the national statistical accident card (defined by the regulation of the Minister of Labor and Social Policy of January 7, 2009 (Journal of Laws of 2009, No. 14, item 80), amended in 2019 by the regulation of the Minister of Family, Labor and Social Policy of June 4, 2019 (Journal of Laws of 2019, item 1106), which contains details (features) on an employee injured in an accident.

This research is focused on the OSH issues as regards wood processing industry. Therefore, records assigned to division 16 *Manufacture of wood and products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials* were selected out of 24 divisions of section C *Manufacturing* according to Polish Classification of Activities. Data on the occupational accidents directly related to the production process, which took place in 2008-2017 throughout Poland, were analyzed.

In the data pre-processing step, variables (the features characterizing injured employees) were selected for the logistic modeling. Records in which the values of certain variables were unknown, undefined, or not available were excluded from the analysis. In order to solve the problem of rare categories and to limit the possibility of expanding the logistics model, the aggregation of values in the set of explanatory variables was proposed, taking into account their substantive meaning.

As declared earlier, *Casualty injury severity* is the explained variable that takes two values: *Serious* and *Other*. The variable is considered as a risk-related OSH measure. According to the literature (Abdalla et al., 2017; Sinclair, Cunningham, 2014), there is a difference in terms of the severity of the effects of occupational accidents (including loss of life) between employees of smaller companies and employees of larger companies. In order to verify whether the above applies to Polish conditions, the Pearson's chi-square test of independence (Howell, 2011) was performed at the significance level of $\alpha = 0.05$. Two variables were considered:

- *Casualty injury severity*.
- *Company size*, determined on the basis of the number of employees as having two values: *wk*1 – for micro and small companies, *wk*2 – for medium and large companies.

The following hypotheses were formulated:

H0: The company size does not affect the occupational accident casualty injury severity.

H1: The company size affects the occupational accident casualty injury severity.

The observed frequencies in both subsets are included in the contingency table (Table 1). The calculated value of the chi-square statistic is 219.05, and the *p-value* < 0.0001. Therefore, the null hypothesis has to be rejected. It can be concluded, with the 95% probability, that the size of the company has an impact on the severity of the occupational accident casualty injury.

Table 1.
The observed frequencies for Company size vs. Casualty injury severity

Casualty injury severity	**Company size**		**Total**
	*wk*1	*wk*2	
Other	2763	7430	10193
Serious	685	1174	1859
Total	3448	8604	12052

Source: authors' own elaboration.

Table 2 summarizes the variables considered in the logistic modeling by the company size. Values of explanatory variables and the codes of these values represent factors that can influence the explained variable. They are later utilized in the interpretation of modeling results. Two logistic models: *M-wk*1 and *M-wk*2 are built independently for data subsets from the two companies: *wk*1 and *wk*2 respectively.

Table 2.
Characteristics of the research data

Variables in the logistic model		***wk*1** [%]	***wk*2** [%]
Explanatory variables	**Factors**	$n = 3448$	$n = 8604$
***P*01 – Casualty gender**			
Male	*P*01_1	92.49	82.44
Female	*P*01_2	7.51	17.56
***P*02 – Casualty age**			
Up to 24 years old	*P*02_1	17.43	17.61
25 - 34 years old	*P*02_2	30.42	30.51
35 - 44 years old	*P*02_3	24.74	25.50
45 - 54 years old	*P*02_4	18.10	18.56
Over 54 years *Aggregation of original values*: (*55 - 59 years*) + (*over 59 years*)	*P*02_5	9.31	7.82
***P*05 – Casualty occupation**			
Industrial workers, craftsmen, and employees doing simple works *Aggregation of original values*: (*Industrial workers and craftsmen*), (*Employees doing simple works*)	*P*05_1	78.94	63.66
Operators and assemblers of machines and devices	*P*05_2	21.06	36.34

Cont. table 2.

***P*06 – Enterprise job seniority**			
Up to 5 years	*P*06_1	69.43	67.18
6 - 10 years	*P*06_2	15.43	16.09
Over 10 years *Aggregation of original values*: (*11-15*), (*16-20*), (*21-30*), (*Over 30 years*)	*P*06_3	15.14	16.74
***P*07 – Hours worked between starting work and the time of the accident**			
0 - 3	*P*07_1	46.61	47.00
4 - 7	*P*07_2	48.72	48.38
8 and more *Aggregation of original values*: (*8-11*), (*12-15*), (*16-19*), (*20-23*)	*P*07_3	4.67	4.61
P*08* – Injury type			
Wounds and superficial injuries	*P*08_1	56.27	62.04
Bone fractures	*P*08_2	19.66	16.00
Displacements, dislocations, sprains and strains	*P*08_3	6.38	12.48
Traumatic amputations (loss of body parts)	*P*08_4	14.68	5.32
Internal injuries	*P*08_5	3.02	4.15
***P*09 – Injured body part**			
Head, neck *Aggregation of original values:* (*Head*), (*Neck with cervical spine*)	*P*09_1	5.02	6.68
Body *Aggregation of original values*: (*Thoracic and lumbar spine*), (*Torso and internal organs*), (*Whole body and its various parts*), (*Other body part*)	*P*09_2	3.16	4.37
Upper limbs	*P*09_3	73.93	68.03
Lower limbs	*P*09_4	17.89	20.92
***P*16 – Season when the accident happened**			
Spring months *Aggregation of original values: (March) + (April) + (May)*	*P*16_1	24.86	25.78
Summer months *Aggregation of original values: (June) + (July) + (August)*	*P*16_2	25.73	24.74
Autumn months *Aggregation of original values: (September) + (October) + (November)*	*P*16_3	24.45	25.35
Winter months *Aggregation of original values: (December) + (January) + (February)*	*P*16_4	24.97	24.13
***P*21 – Activity performed at accident time**			
Operating machinery	*P*21_1	57.05	44.97
Working with tools and objects *Aggregation of original values*: (*Working with hand tools*), (*Handling objects*)	*P*21_2	25.49	30.85
Transport at workplace *Aggregation of original values*: *(Driving means of transport / operation of moving machines and other devices), (Manual transporting)*	*P*21_3	12.24	14.81
Being at accident scene *Aggregation of original values*: (*Moving about*), (*Presence)*	*P*21_4	5.22	9.38
***P*26 – Material factor as injury source**			
Buildings, structures, surfaces *Objects as above and their elements including positions*: (*At ground level*), (*Below ground level*), (*Above ground level*)	*P*26_1	5.83	8.18
Waste	*P*26_2	1.80	1.84
Hand tools *Aggregation of original values*: (*Non-powered hand tools*), (*Hand-held or hand guided mechanized tools*)	*P*26_3	11.02	9.75
Machines and devices *Aggregation of original values*: (*Portable or mobile machines and equipment*), (*Stationary machines, devices and equipment*), (*Machines, devices and equipment for lifting, carrying and storage*)	*P*26_4	50.84	40.49
Materials, objects, products, machine parts	*P*26_5	30.51	39.74

Cont. table 2.

***P*27 – Main accident cause**			
Defect of material factor *Aggregation of original values*: (*Design defects or inappropriate technical and ergonomic solutions of material factor*), (*Improper manufacturing of material factor*), (*Material defects of material factor)*	*P*27_1	21.75	14.39
Misuse of material factor *Aggregation of original values*: (*Inappropriate exploitation of material factor*), (*Employee's non-use or inappropriate handling of material factor*)	*P*27_2	14.36	14.53
Inappropriate work organization *Aggregation of original*: (*Inadequate overall organization of work*), (*Inappropriate organization of a workplace*), (*Employee's failure to use protective equipment*)	*P*27_3	10.99	11.91
Safety neglect *Aggregation of original values*: (*Employee's psychophysical state, not ensuring safe work performance*), (*Employee's inappropriate arbitrary behavior*), (*Employee's misconduct*)	*P*27_4	52.90	59.17
Explained variable	**Value**	***wk*1** [%]	***wk*2** [%]
***P*289 – Casualty injury severity**			
Other *Aggregation of original values*: (*Minor accident resulting in inability to work for 0-13 days*), (*Minor accident resulting in inability to work for 14-29 days*), (*Minor accident resulting in inability to work for 30-89 days*)	Failure	80.13	86.36
Serious *Aggregation of original values*: (*Severe or fatal accident*), (*Minor accident causing inability to work for more than 90 days*)	Success	19.87	13.65

Source: authors' own elaboration.

4. Logistic regression models for occupational accidents by the company size

Table 3 shows the logistic models assessment. The results of model significance test indicates that both models, *M-wk*1 and *M-wk*2, which classify casualty injury severity, are statistically significant at $\alpha = 0.05$. The complexity of the full logistic models (*FM* – all explanatory variables included) combined with the relatively small size of the balanced training data sets was reflected in the *AIC*(*FM*) and *SBC*(*FM*) values greater than the corresponding values of the *AIC*(*SM*) and *SBC*(*SM*) values for the stepwise models (*SM* – selected explanatory variables included). These results indicate that in each case, the stepwise model (*SM*) is better than the full model (*FM*). The introduction of balancing to the training data set made it possible to estimate the models in which the infrequent value of the success category (*Serious*) was well classified, while the classification of the failure category (*Other*) was not deteriorated. The model quality assessment is satisfactory for all data sets. *PCC* exceeds the value of 0.66. However, the classifications of individual values of the explained variable are important. The *TPR* (*Serious* → *Serious*) index values are equal to 0.62 and 0.67, and the *TNR* (*Other* → *Other*) index value are about 0.71 and 0.70 for the *M-wk*1 and *M-wk*2 models respectively, for both the balanced and imbalanced data sets. The good quality of the classifiers is confirmed in particular by the *TPR* and *TNR* indices for the test data set, ranging from 0.56 to 0.73, which is further supported by the *HMSS* index values of 0.64 and 0.68 for *M-wk*1 and *M-wk*2 respectively.

Table 3.
Assessment measures for the M-wk1 and M-wk2 logistic models

Assessment measure	*M-wk*1			*M-wk*2		
	Balanced training data	Test data	Imbalanced training data	Balanced training data	Test data	Imbalanced training data
Lik. Ratio Chi-Square DF *p-value*	147.155 7 <0.0001	–	–	317.272 15 <0.0001	–	–
AIC(FM)	1215.91	–	–	2005.70	–	–
AIC(SM)	1196.91	–	–	1991.02	–	–
SBC(FM)	1366.72	–	–	2173.22	–	–
SBC(SM)	1235.83	–	–	2077.48	–	–
Number of observations	958	1035	2413	1642	2583	6021
Percentage *Serious* *Other*	 50% 50%	 19.90% 80.10%	 19.85% 80.15%	 50% 50%	 13.67% 86.33%	 13.64% 86.36%
Serious → Serious	0.624	0.568	0.624	0.664	0.671	0.664
Serious → Other	0.376	0.432	0.376	0.336	0.329	0.336
Other → Serious	0.292	0.274	0.285	0.302	0.310	0.309
Other → Other	0.708	0.726	0.715	0.698	0.690	0.691
PCC	0.666	0.695	0.697	0.681	0.687	0.687
HMSS	0.663	0.637	0.666	0.680	0.680	0.677

Source: authors' own elaboration.

Table 4 present the results of stepwise selection applied to 11 explanatory variables considered in the logistic modeling. The model for medium and large enterprises (*M-wk*2) is more extended than that for micro and small enterprises (*M-wk*1). The following variables turned out to be statistically significant:

- for the *M-wk*1 model: *P*08 (*Injury type*), *P*21 (*Activity performed at accident time*),
- for the *M-wk*2 model: *P*02 (*Casualty age*), *P*08 (*Injury type*), *P*21 (*Activity performed at accident time*) and *P*26 (*Material factor as injury source*).

Table 4.
The results of stepwise selection for the M-wk1 and M-wk2 logistic models

Variable	*M-wk*1			*M-wk*2		
	DF	Wald Chi-square	p-value	DF	Wald Chi-square	p-value
*P*02	–	–	–	4	29.09	<0.0001
*P*08	4	104.063	<0.0001	4	184.19	<0.0001
*P*21	3	22.345	<0.0001	3	8.85	0.0314
*P*26	–	–	–	4	21.62	0.0002

Source: authors' own elaboration.

Using odds ratios obtained from the logistic models makes it possible to determine how the possibility that an occupational accident casualty was seriously injured changed with the indicated change in the value of the explanatory variable while the other variable values are held fixed (ceteris paribus). Table 5 contains information about the odds ratios. Non significant factors (*p-value* = 0.05) are marked by a gray background and they are omitted in the interpretation. The interpretation of the odds ratio of each significant factor, controlling for other factors, is given in relation to the reference values of individual explanatory variables. Figure 1 shows a graphical illustration of the modeling results.

According to the *M-wk*1 model, the odds of the serious occupational accident casualty injury are:

- in the case of *Injured body part*:
  - for *Bone fractures* over three times greater than for *Wounds and superficial injuries*; *OR*(*P*08_2 vs. *P*08_1) = 3.376,
  - for *Displacements, dislocations, sprains and strains* two times greater than for *Wounds and superficial injuries*; *OR*(*P*08_3 vs. *P*08_1) = 2.166,
  - for *Traumatic amputations* six times greater than for *Wounds and superficial injuries*; *OR*(*P*08_4 vs. *P*08_1) = 6.190,
  - for *Internal injuries* two and a half times greater than for *Wounds and superficial injuries*; *OR*(*P*08_5 vs. *P*08_1) = 2.462,
- in the case of *Activity performed at accident time*:
  - for *Working with tools and objects* by almost 50% smaller than for *Operating machinery*; *OR*(*P*21_2 vs. *P*21_1) = 0.521,
  - for *Transport at workplace* by nearly 60% smaller than for *Operating machinery*; *OR*(*P*21_3 vs. *P*21_1) = 0.431.

According to the *M-wk*2 model, the odds of the serious occupational accident casualty injury are:

- in the case of *Casualty age*:
  - for workers *Up to 24 years old* by over 60% smaller than for workers *Over 54 years*; *OR*(*P*02_1 vs. *P*02_5) = 0.367,
  - for *25 - 34 years old* workers by 50% smaller than for workers *Over 54 years*; *OR*(*P*02_2 vs. *P*02_5) = 0.488,
  - for *35 - 44 years old* workers by 40% smaller than for workers *Over 54 years*; *OR*(*P*02_3 vs. *P*02_5) = 0.587,
- in the case of *Injured body part*:
  - for *Bone fractures* almost five times greater than for *Wounds and superficial injuries*; *OR*(*P*08_2 vs. *P*08_1) = 4.704,
  - for *Displacements, dislocations, sprains and strains* almost three times greater than for *Wounds and superficial injuries*; *OR*(*P*08_3 vs. *P*08_1) = 2.708,
  - for *Traumatic amputations* nearly ten times greater than for *Wounds and superficial injuries*; *OR*(*P*08_4 vs. *P*08_1) = 9.841,
  - for *Internal injuries* three times greater than for *Wounds and superficial injuries*; *OR*(*P*08_5 vs. *P*08_1) = 2.993,

- in the case of *Activity performed at accident time*:
  - o for *Working with tools and objects* by slightly over 30% smaller than for *Operating machinery*; *OR*(*P*21_2 vs. *P*21_1) = 0.681,
- in the case of *Material factor as injury source*:
  - o for *Buildings, structures, surfaces* by 45% smaller than for *Machines and devices*; *OR*(*P*26_1 vs. *P*26_4) = 0.555,
  - o for *Hand tools* by slightly under 50% smaller than for *Machines and devices*; *OR*(*P*26_3 vs. *P*26_4) = 0.513,
  - o for *Materials, objects, products, machine parts* by over 40% smaller than for *Machines and devices*; *OR*(*P*26_5 vs. *P*26_4) = 0.584.

The same variables are present in both of the models: *Injury type* (*P*08) and *Activity performed at accident time* (*P*21). Considering *P*08, there is the same tendency as regards the magnitude of the injury type influence on the consequences of an accident at work. The importance of the *P*08 effect for medium-sized and large companies is greater than for micro and small companies, as shown by the corresponding odds ratios for the individual factors. In both cases, the impact of the reference category *Wounds and superficial injuries* (*P*08_1) is smaller than all other types of injury. The fact that *Traumatic amputations* (*P*08_4) have the greatest positive impact on the injury severity is intuition-consistent, but the magnitude of this impact is meaningful, several times greater than the other injury types. For the variable *P*21, the reference category *Operating machinery* (*P*21_1) identifies a greater risk for occupational safety than the other statistically significant activities; *Working with tools and objects* (present in both models *M-wk*1 and *M-wk*2) and *Transport at workplace* (only in *M-wk*1). The *Working with tools and objects* factor (*P*21_2) has a greater negative impact on the success value of the explained variable in model *M-wk*1 than in model *M-wk*2. The *M-wk*2 model includes two more variables, absent in the *M-wk*1 model: *Casualty age* (*P*02) and *Material factor as injury source* (*P*26).

Table 5.
The odds ratios for the M-wk1 and M-wk2 logistic models

Parameter	***M-wk*1**				***M-wk*2**			
	Value	**Standard error**	**p-value**	**Odds ratio**	**Value**	**Standard error**	**p-value**	**Odds ratio**
Intercept	-0.489	0.115	<0.0001	-	0.240	0.204	0.24	-
*P*02_1	-	-	-	-	-1.003	0.241	<0.0001	0.367
*P*02_2	-	-	-	-	-0.717	0.216	0.0009	0.488
*P*02_3	-	-	-	-	-0.533	0.212	0.0119	0.587
*P*02_4	-	-	-	-	-0.192	0.220	0.3838	0.826
*P*02_5	-	-	-	-	Reference value			
*P*08_2	1.217	0.177	<0.0001	3.376	1.548	0.148	<0.0001	4.704
*P*08_3	0.773	0.303	0.011	2.166	0.996	0.174	<0.0001	2.708
*P*08_4	1.823	0.199	<0.0001	6.190	2.287	0.238	<0.0001	9.841
*P*08_5	0.901	0.374	0.016	2.462	1.096	0.236	<0.0001	2.993

Cont. table 5.

*P*08_1	Reference value							
*P*21_2	-0.652	0.171	0.0001	0.521	-0.385	0.145	0.008	0.681
*P*21_3	-0.841	0.247	0.0007	0.431	-0.236	0.175	0.177	0.790
*P*21_4	-0.031	0.300	0.919	0.970	0.067	0.215	0.757	1.069
*P*21_1	Reference value							
*P*26_1	-	-	-	-	-0.589	0.227	0.009	0.555
*P*26_2	-	-	-	-	-0.301	0.444	0.499	0.740
*P*26_3	-	-	-	-	-0.668	0.242	0.006	0.513
*P*26_5	-	-	-	-	-0.537	0.128	<0.0001	0.584
*P*26_4	-	-	-	-	Reference value			

Source: authors' own elaboration.

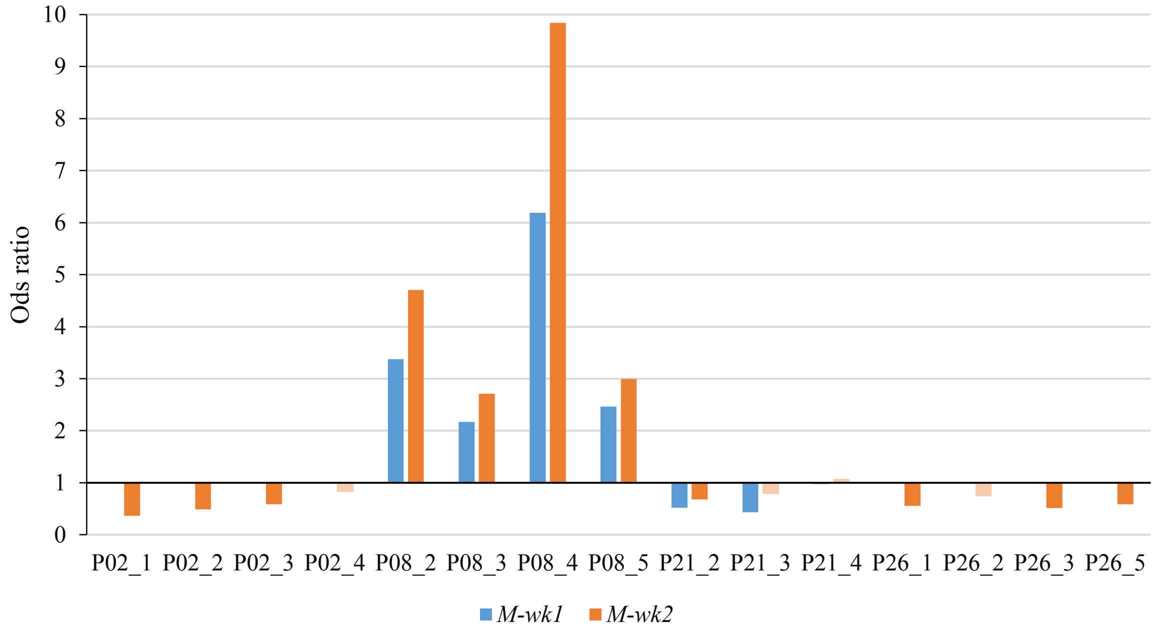

Figure 1. The comparison of the *M-wk*1 and *M-wk*2 logistic models results.

Source: authors' own elaboration.

5. Conclusions

Each type of economic activity carries various hazardous situations as regards occupational safety. Some of them generate greater danger for an employee than other. Although wood processing industry is an economy sector with a relatively high risk of accidents at work, the problem is discussed in few publications.

In this study, factors that can influence the injury severity of the occupational accident casualty in wood processing companies were investigated using logistic regression. It was shown in the work that the enterprise size had an impact on the severity of accidents at work. Therefore, logistic models were developed for enterprises classified into two groups: (1) micro and small and (2) medium and large. Using odds ratios, explanatory variables in logistic models were interpreted according to their importance and intensity of influence on the value of the explained variable.

Among the 11 analyzed variables, many of them were not identified as important in the logistic models, in the stepwise selection procedure. In particular, there were: *Enterprise job seniority* or *Injured body part*. It is possible that their explanatory role may have been taken over by variables significant in the models.

In larger workplaces, all types of injuries as referenced to *Wounds and superficial injuries* were identified as having a greater impact on the outcome of an occupational accident than in smaller workplaces. This could indicate that medium and large enterprises experience more safety climate problems than micro and small companies.

The greatest risk regarding *Activity performed at accident time* in both types of enterprises was created by *Operating machinery*. Inadequate initial or job training, or scant machines and devices maintenance, or insufficient equipment of the machine with safety elements are the likely explanations for such findings. These circumstances can also refer to handling of potentially dangerous *Machines and devices* identified as the most risky *Material factor as injury source*, but only in larger enterprises, which may be caused by higher pressure and pace of work.

In larger companies, workers over the age of 54 were more likely to be seriously injured in occupational accidents than workers of any other age. This may be due to routine or habitual neglect of risk factors at work, but also physical or mental exhaustion, which can be accompanied by lack of or poor supervision.

The research showed that bivariate multiple logistic regression is an appropriate tool for analyzing occupational accident data. The obtained results can be used in the development of materials on occupational safety risks for entrepreneurs and OSH services.

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