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Examining the Determinants of Occurrence of Accidents at the Construction Phase in Oil, Gas and Petrochemical Projects: (A Case Study of Assaloyeh)

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Abstract: In this study, a count-data regression is presented to estimate and analyze the effects of determinant factors affecting the accidents leading to death, through negative binomial regression. For this purpose the structure of 50 accidents that led to death and another 2700 accidents in the Construction Phase in Oil, Gas and Petrochemical Projects (a case study of Assaloyeh) during 2003-2005 has been studied. Along with total accidents, unsafe conditions, human errors, management faults and using nonstandard equipments, were considered as the main independent variables affecting the job accidents leading to death, as the dependent variable. By employing the method of developing abstract variables and taking values (codes) one and zero (zero for lack of quality and one for its existence), the variables were quantified. EViews software has been employed, because it provides support for the estimation of several models of count data. The findings of the study show that for each number increase in the unsafe conditions, human errors and either nonstandard equipments or management faults, the expected number of deadly accident increases by a factor of 0.2982 and 0.1137 as well as 0.0259, respectively. If the number of total accidents increases by one unit, the difference in the logs of expected counts would be expected to increase by 0.0025 unit, while holding the other variables in the model constant. Apart from such predictors, the log of the expected count for deadly accidents is 0.0023.

Key words: Count data regression, negative binomial model, deadly accidents, Assaloyeh

INTRODUCTION

Based on an assessment by International Labor Office, 180,000 individuals die in the work accidents in the industries per year, while 110 million people are injured (Famoye, 2004; Hautzinge, 1987). On the other hand, construction phase in industries is a dynamic process that is naturally and intrinsically dangerous and as it becomes more complicated, the accidents rate increases. According to OSHA International Organization, the number of accidents led to death at these industries is more than 2000 death per year in average (James and Fullman, 1994; John and Marvin, 2000).

In average, of each six construction labors, one is suffering from job damages and illnesses per year and of each 16 individuals, one becomes seriously damaged. In average, the construction labors miss about 1.2 days per year of their work as a result of damages in the work (Lars Harms, 2001).

The construction phase of oil, gas and petrochemical projects is facing to a large spectrum of challenges; one of those challenges is the frequent accidents. From the starting date of these projects (around four years ago), many accidents have been occurred and a significant number of accidents (50) led to death and many others ended with disability damages. Applying the accidents study pyramid to such a subject will show the great importance of the subject. As an example, by using the Tye/Pearson pyramid (1974-1975) where per each accident leading to death or serious incidents in the world, thirty accidents were minor, fifty accidents needed first aids, eighty accidents led to damages to facilities and properties and four hundred were semi-accident. With a simple calculation, one might note that during this period, per each minimum 50 accidents leading to death, there have been 1500 minor accidents, 2500 accidents needing first aids, 4000 accidents damaging facilities and properties and 20000 semi-accident incidents. These values and numbers show the fact that construction is a high-risk region. Then it is needed to develop a proper strategy to lower the rate of accidents in those projects. However, knowing the factors and causes of those

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accidents are more important than calculating the total number of accidents leading to death. This information could be used in the expansion and development of a plan to improve the safety level in construction phase through decreasing accident rate. On the other hand, with respect to the important fact that occurrence of large accidents in this industry (which is unique in Iran as well) might disconnect the production chain in many other industries and cause huge loss. Therefore, we should make a careful evaluation of the nature of energies and the risks involved in them in order to take suitable controlling approaches. The major goals of this research are:

- Study and identification of major and effective factors in the occurrence of accidents leading to death and disability in the system subject of study;
- To present a mathematical model to estimate increase in work environment as a result of any of the predicted factors (regression analytical method)

In this research, it is tried to carry out a comprehensive study of risk assessment and by studying and identifying the main and effective accidents that lead to death and disability in the system subject of study, develop a mathematical model for assessing increase in work environment as a result of each one of the predicted factors.

Concerning the factors that affect different accidents by regression analytical method, considerable empirical studies have been performed, followings are some of them Famoy (2004) studied the effects of environmental factors, driving habits and medical cares in car accidents in Alabama by using regression models (Ludwig, 1985).

Hautzinger (1987) studied safety in traffic by using regression analysis (National Safety Council, 1992).

- Wegni and Ross (2004) studied volume of hospital accidents and emergency accidents caused by air pollution in Europe.

The results of the research, with using regression analysis, showed that despite high air pollutions and affecting the health of society, one could not measure the accidents caused by air pollution in micro level, easily (Steve, 2004).

MATERIALS AND METHODS

Model is an abstract terminal (mathematical, physical or graphical) that follows special regulations and standards. The model is the reflection of a fact. In another expression, it should be said that the model represents a system or process that could predicted the behavior of that system or process. Therefore, models are used for understanding the behavior of actual terminal and show a theory in the way that covers important variables for describing phenomena and instead, ignores factors with low importance in the expression of those phenomena.

One should note that without considering the model, one could not obtain useful and reliable method to prevent accidents; therefore, to achieve useful methods in preventing accident, it is desirable to consider models on the quality of accident (Trevor, 1988).

In this research count model has been employed since the dependent variable (FNOAC) takes integer values that represent the number of events that occur over a fixed time interval. To estimate the count model EViews has been employed, because EViews provides support for the estimation of several models of count data. In addition to the standard Poisson and negative binomial Maximum Likelihood (ML) specifications, EViews provides a number of Quasi-Maximum Likelihood (QML) estimators for count data. In the case of count data, Poisson mode is a common model used to estimate the parameters of the model.

For the Poisson model, the conditional density of y_i given is:

$$f(y_i \mid x_i, \beta) = e^{-m(x_i,\beta)}\, m(x_i, \beta)^{y_i} / y_i| \qquad (1)$$

where y_i is a non-negative integer valued random variable. The maximum likelihood estimator (MLE) of the parameter β is obtained by maximizing the log likelihood function:

$$1(\beta) = \sum_{i=1}^{N} y_i \log m(x_i,\beta) - m(x_i,\beta) - \log(y_i|) \qquad (2)$$

Provided the conditional mean function is correctly specified and the conditional distribution of y is Poisson, the MLE $\hat{\beta}$ is consistent, efficient and asymptotically normally distributed, with variance matrix consistently estimated by:

$$V = \mathrm{var}(\hat{\beta}) = (\sum_{i=1}^{N} (\frac{\partial \hat{m}_i}{\partial \beta}\frac{\partial \hat{m}_i}{\partial \beta}) / \hat{m}_i)^{-1} \qquad (3)$$

where: $\hat{m}_i = m(x_i, \hat{\beta})$

The most important restriction is the equality of the (conditional) mean and variance:

$$v(x_i,\beta) = \mathrm{var}(y_i \mid x_i \beta) = E(y_i \mid x_i \beta) = m(x_i,\beta) \qquad (4)$$

If the mean-variance equality does not hold, the model is misspecified. To test this equality deviance and Pearson Chi-Square divided by the degrees of freedom are used in the Poisson regression. Values greater than 1 indicate overdispersion, that is, the true variance is bigger than the mean and values smaller than 1 indicate underdispersion, i.e. the true variance is smaller than the mean. Evidence of underdispersion or overdispersion indicates inadequate fit of the Poisson model. We can test for overdispersion with a likelihood ratio test based on Poisson and negative binomial distributions. This test, tests equality of the mean and the variance imposed by the Poisson distribution against the alternative that the variance exceeds the mean. For the negative binomial distribution, the variance = mean+k mean2 (k> = 0, the negative binomial distribution reduces to Poisson when k = 0). The null hypothesis is:

H0: k = 0 and the alternative hypothesis is: H1: k>0.

To carry out the test, we use the LR (likelihood ratio) test, that is, compute LR statistic as -2(LL (Poisson)-LL (negative binomial).The asymptotic distribution of the LR statistic has probability mass of one half at zero and one half-Chi-sq distribution with one df. 1 To test the null hypothesis at the significance level 2α, use the critical value of Chi-sq distribution corresponding to significance level 2α, that is reject H_0 if LR statistic>$\chi^2_{(1-2\alpha,\ 1\ df)}$.

The calculated LR statistic (26.72) is greater than the critical value of χ^2 (2.71). This indicates overdispersion and inadequate fit of the Poisson model. When there is overdispersion in the data, one common alternative to the Poisson model is to estimate the parameters of the model using maximum likelihood of a negative binomial specification. The log likelihood for the negative binomial distribution is given by:

$$
\begin{aligned}
1(\beta,\eta) = \sum_{i=1}^{N} & y_i \log(\eta^2 m(x_i,\beta)) \\
& -(y_i + 1/\eta^2)\log(1+\eta^2 m(x_i,\beta)) \\
& +(\log\Gamma(y_i + 1/\eta^2) - \log(y_i) - \log\Gamma(1/\eta^2)
\end{aligned}
\tag{5}
$$

where η^2 is a variance parameter to be jointly estimated with the conditional mean parameters β.

The following table presents the results obtained from estimating the parameters of the model using maximum likelihood of a negative binomial specification. The Robust Covariance of the estimation has been computed by the Huber/White method using Newton-Raphson optimization algorithm to correct standard errors for overdispersion.

Table 1: Estimation results of negative binomial (QML) model

Dependent variable: FNOAC
Method: QML-Negative Binomial Count (Quadratic hill climbing)
Date: 12/12/06 Time: 09:34
Sample: 1382 M01 1384 M10 IF FNOAC>0
Inclided observation: 24
QML parameter used in estimation: 1
Convergence achieved after 5 iteration
QML (Huber/White) standard errors and convariance

Variables	Coefficient	Std. Error	z-statistic	Prob
C	0.002337	0.000883	2.647251	0.0081
TACS	0.0025212	0.001279	1.964390	0.0511
UNA	0.113689	0.035863	3.170087	0.0015
UNC	0.298253	0.077684	3.839315	0.0001
MNGEQUP	0.025950	0.013494	1.923027	0.0545
R-squared	0.851966	Mean dependent var		2.125000
Adjusted R-squared	0.820801	SD dependent		1.261900
SE of regression	0.534187	Akaike info criterion		4.299963
Sum squared rresid	5.421751	Schwarz criterion		4.545391
Log likelihood	-46.59956	Hannan-Quinn criter		4.365075
Restr. log likelihood	-51.38185	Avg. log likelihood		-1.941648
LR statistic (4 df)	9.564578	LR index (Pseudo-R2)		0.093074
Probability (LR stat)	0.04837			

The response variable is the number of deadly accidents (i.e., accidents lead to death or major injury (FNOAC)), from which we explore its relationship with the total accidents (TACS), human errors (UNA), insecure conditions (UNC) and either using nonstandard equipments or applying improper management (MNGEQUO). Therefore, in Table 1, FNOAC is the response variable in the negative binomial regression and underneath FNOAC are the predictor variables and the intercept (C).

The result show that the estimated model is as follow.

FNOAC = 0.0023+0.0025 TACS+0.1137 UNA+0.2982UNC +0.0259 MNGEQUP

As shown in the Table 1, the resulting adjusted R-squared value is 0.82 may indicate a very close fit to the data. It seems that about 82% of variation in FNOAC is explained by the model.

The LR test statistic is used for the omnibus test that at least one predictor variable regression coefficient is not equal to zero in the model. The small p-value from the LR test (p = 0.048) leads us to conclude that at least one of the regression coefficients in the model is not equal to zero.

All coefficients have the expected signs and are statistically significant at 5% p-level.

TACS is the negative binomial-regression estimate for a one unit increase in number of total accidents, given the other variables are held constant in the model. If the number of total accidents increases by one unit, the difference in the logs of expected counts would be expected to increase by 0.0025 unit, while holding the other variables in the model constant. It means that for each number increase in the total accident the expected number of deadly accident increase by a factor of 0.0025. UNA and UNC as well as MNGEQUP are other negative binomial-regression estimates for a one unit increase in number of human errors and the number of insecure conditions as well as the number of nonstandard equipments and management faults. For each unit increase in the human errors the expected number of deadly accident increases by a factor of 0.1137. Similarly, for each unit increase in the insecure conditions the expected number of deadly accident increases by a factor of 0.2982. By the same token, for each unit increase in either nonstandard equipment or management fault the expected number of deadly accident increases by a factor of 0.0259.

C is also a negative binomial-regression estimate for a one unit increase when all variables in the model are evaluated at zero. Therefore, if there are no such predictors, the log of the expected count for deadly accidents is 0.0023.

RESULTS AND DISCUSSION

Results of assessing the above-mentioned model could answer following questions:

- Do the unsafe conditions and unsafe functions (disregarding standards before, during and after work) have any effects on the percentage of work environment accidents? If this factor is effective, how much is the percent of increase in job accidents leading to death because of increase in the percentage of unsafe conditions and unsafe functions?
- Do the undesirable managerial factors have any effects on the percentage of accidents in work environment? If this factor is effective, what is the percent of increase in job accidents leading to death as a result of increase in the undesirable managerial factors?
- Does the use of standard and sound facilities, materials and machinery have any effects on the percentage of accidents in work environment? If this factor is effective, what is the percentage of increase in job accidents leading to death, as a result of increase in this factor?
- Are there any other variables rather than predicted independent variables that might play any role in job accidents leading to death?

The result show that the estimated model is as follow.

$$FNOAC = 0.0023 + 0.0025\,TACS + 0.1137\,UNA + 0.2982\,UNC + 0.0259\,MNGEQUP$$

As shown in the above table, the resulting adjusted R-squared value is 0.82 may indicate a very close fit to the data. It seems that about 82% of variation in FNOAC is explained by the model.

The LR test statistic is used for the omnibus test that at least one predictor variable regression coefficient is not equal to zero in the model. The small p-value from the LR test ($p = 0.048$) leads us to conclude that at least one of the regression coefficients in the model is not equal to zero.

All coefficients have the expected signs and are statistically significant at 5% p-level.

TACS is the negative binomial-regression estimate for a one unit increase in number of total accidents, given the other variables are held constant in the model. If the number of total accidents increases by one unit, the difference in the logs of expected counts would be expected to increase by 0.0025 unit, while holding the other variables in the model constant. It means that for each number increase in the total accident the expected number of deadly accident increase by a factor of 0.0025. UNA and UNC as well as MNGEQUP are other negative binomial-regression estimates for a one unit increase in number of human errors and the number of insecure conditions as well as the number of nonstandard equipments and management faults. For each unit increase in the human errors the expected number of deadly accident increases by a factor of 0.1137. Similarly, for each unit increase in the insecure conditions the expected number of deadly accident increases by a factor of 0.2982. By the same token, for each unit increase in either nonstandard equipment or management fault the expected number of deadly accident increases by a factor of 0.0259.

C is also a negative binomial-regression estimate for a one unit increase when all variables in the model are evaluated at zero. Therefore, if there are no such predictors, the log of the expected count for deadly accidents is 0.0023.

CONCLUSIONS

Work accidents in the World are very high, to the extent that 180,000 individuals die in the work accidents in the industries each year and 10 million people are injured. The rate of such accidents in the industrial construction phase is naturally and intrinsically mostly high. The number of accidents led to death at these industries is more than 2000 death per year in average. Because of this, it became necessary to examine the determinants affecting the work accidents in such industries. In this study, a count-data regression has been applied to estimate and analyze the effects of determinant factors affecting the accidents leading to death, through negative binomial regression. To this end the 2750 accidents in the Construction Phase in Oil, Gas and Petrochemical Projects of Assaloyeh as a case study has been studied. The period of the study is 2003-2005. Along with total accidents, unsafe conditions, human errors, management faults and using nonstandard equipments, were considered as the main independent variables affecting the work accidents leading to death, as the dependent variable. EViews software has been employed to estimate several models of count data. The findings of the study show that for each number increase in the unsafe conditions, human errors and either nonstandard equipments or management faults, the expected number of deadly accident increases by a factor of 0.2982 and 0.1137 as well as 0.0259, respectively. If the number of total accidents increases by one unit, the difference in the logs of expected counts would be expected to increase by 0.0025 unit, ceteris paribus. Apart from such predictors, the log of the expected count for deadly accidents is 0.0023.

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