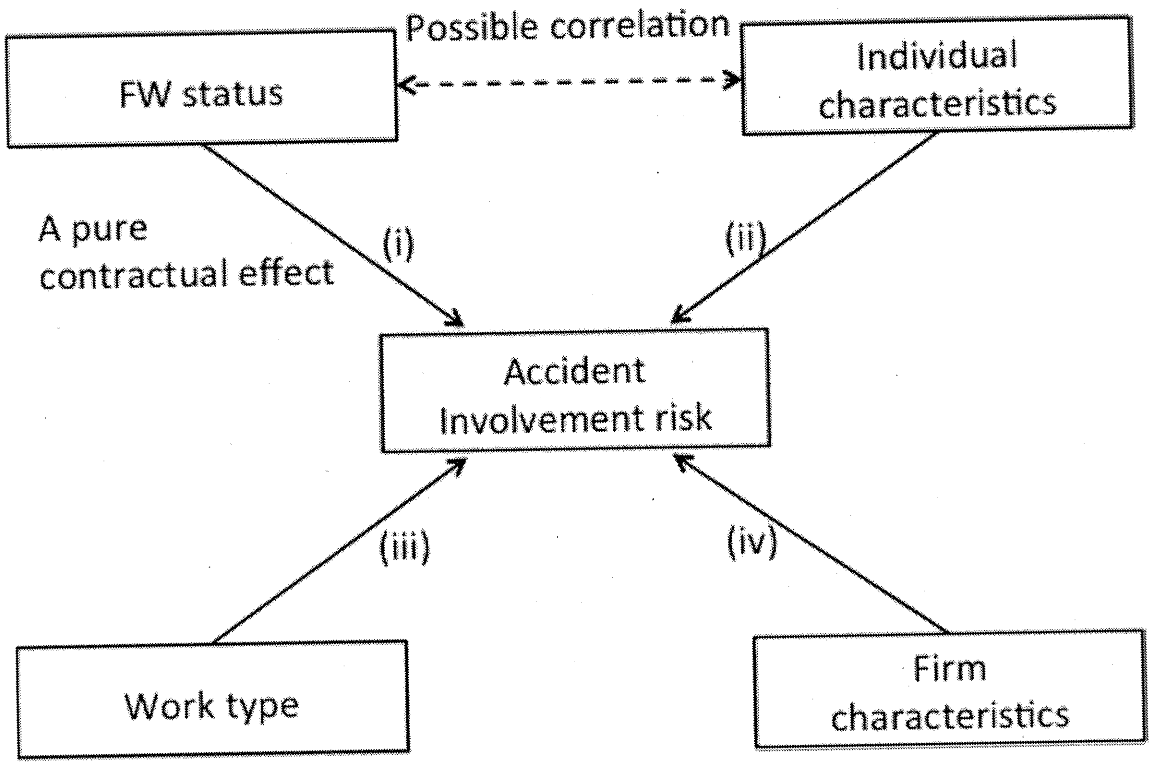

Figure 1 Conceptual model of the FW's occupational accident involvement risk

The information on factors influencing occupational accident occurrences suggests an important implication for accident reduction measures. In the case where a pure contractual effect is the main cause of FW accidents, a change in employment strategy would be effective in reducing the number of accidents. For example, Guadalupe (2003) notes, "a policy implication of these results [i.e., the existence of a pure contractual effect] would be to try to limit the use of FTC [fixed term contracts] to cases where it is really necessary and bring in labour market flexibility using another type of institution that does not have this negative feature. Or set up the conditions so that more FTCs are transformed into permanent contracts and the mechanisms through which the pure contractual effect appears are no longer present." In the case where the cause of accidents is, for example, lesser work experience, it would be ineffective to change FWs to PWs for accident reduction. In that case, increasing employee work experience would be necessary as a long-term solution, and compensating for their lack of experience would be necessary as a short-term solution. In any case, we should design appropriate accident reduction measures based on the actual causes of accidents.

This article is organized as follows: the data collection method and the data's character are described in Section 2; the statistical model is explained in Section 3; the estimation results are presented in Section 4; and some concluding remarks are made in Section 5.

2 Data collection through an Internet survey

In this study, we conducted an Internet survey to collect data about the accident involvement frequency, individual characteristics, and firm characteristics, of many workers. There are two main reasons why we used an Internet survey as the data collection method. First, most of the data required by the study could not be obtained from public databases. Although the Labor Standards Inspection Offices possess individual-level data on occupational accidents all over Japan, for insurance services, these data are not available for research purposes, owing to personal information protection. Second, an Internet survey offered a far more efficient use of research resources: we could acquire data on roughly 3,000 workers relatively inexpensively, by constructing the data collection web site appropriately.

2-1 Procedure of the survey

The Internet survey was conducted from March 18-22, 2011. With the exception of the Cognitive Failures Questionnaire described below, all the questionnaires were developed by the author. The survey implementation (e.g., web site design, sampling of respondents, setting rewards for respondents, etc.) was outsourced to the research company, Nikkei Research Inc. Nikkei Research Inc. has roughly 169,340 registrants, including people with various backgrounds, and these constituted the parent population of the survey.

Nikkei Research Inc. sent emails to 23,957 registrants and asked them to respond to a "questionnaire about your daily life and job." In order to encourage the respondents to answer the questionnaires, the company announced that 200 respondents would be selected in a draw to receive 500 yen (roughly $US 6.50 at the currency rate as of November 1, 2011) as a reward. The respondents were limited to paid workers who were employed as of March 2011. Unemployed workers, agricultural workers, silvicultural workers, fishery workers, self-employed workers, students, homemakers, and retirees were excluded from the parent population in this study. It is important to note that respondents might be biased in either of two respects: as Internet users, and as intentional registrants for surveys implemented by Nikkei Research Inc.

2-2 Data description

In this section, we will describe the key data collected in the Internet survey and used as variables in the statistical analysis. In addition, the motivation for using these variables in our statistical analysis will be explained.

2-2-1 Accident involvement frequency

(*VARIABLE NAME*) : (Description)

ACCIDENT_FREQ : A respondent's occupational accident involvement frequency over the last five years (March 2006 - February 2011) in their current workplace [times]

As mentioned earlier, it is very difficult to utilize official statistics concerning occupational accidents, owing to personal information protection. Therefore, the relevant data was obtained from respondents' self-reported experience. In this study, occupational accidents were limited to those in which the resulting injury was severe enough that the injured worker was forced to seek medical attention. If the severity of the injuries varies widely, we would have difficulty interpreting the results of the statistical analysis. Therefore, we excluded accidents in which the damage from the injury was comparatively insignificant. *ACCIDENT_FREQ* is expressed by discrete count data using zero or positive integers, and appears as the dependent variable in our regression model, explained in Section 3.

2-2-2 A pure contractual effect

FW : If a respondent is a flexible worker, $FW = 1$; if not, $FW = 0$.

We are interested in whether a pure contractual effect exists; in other words, whether being an FW *per se* affects the worker's involvement risk in occupational accidents. As mentioned in Section 1, only Guadalupe (2003) questioned the existence of a pure contractual effect, and concluded that it did exist. The presence or absence of a pure contractual effect has implications for accident reduction measures. In our statistical model, explained in Section 3, *FW* is used as a dummy variable representing whether a respondent is an FW or a PW.

2-2-3 Individual characteristics

AGE	: Respondent's age [years old]
GENDER	: If a respondent is male, *GENDER* = 1; if not, *GENDER* = 0.
INCOME	: Income in 2010 [million yen]
EXPERIENCE	: Length of continuous respondent experience in their current workplace [years]
WORK_HOURS	: Total work hours over the last five years (March 2006 - February 2011) in the current workplace [hours]
SAW_VIO_PENALTY	: If a respondent has seen workers in his/her workplace being punished for rule violation, *SAW_VIO_PENALTY* = 1; if not, *SAW_VIO_PENALTY* = 0.
SAW_ACCIDENT	: If a respondent has seen workers in his/her workplace being injured in occupational accidents, *SAW_ACCIDENT* = 1; if not, *SAW_ACCIDENT* = 0.
DISLIKE	: If a respondent dislikes his/her job, *DISLIKE* = 1; if not, *DISLIKE* = 0.
STRESS	: If a respondent feels stress about his/her job, *STRESS* = 1; if not, *STRESS* = 0.

AGE, *GENDER*, and *INCOME* were collected as basic information about a respondent. The extant literature regards worker experience as one of the fundamental factors affecting the accident involvement frequency of workers. We will examine whether this factor still has an impact on accident involvement frequency when the influence of other factors are statistically controlled. Typically, the longer a worker belongs to a workplace, the more his/her work skills increase. On the other hand, long and customary experience may lull experienced workers into a false sense of security. Which effect dominates the other, and under what circumstances, is an empirical question. *WORK_HOURS* was calculated as work years over the last 5 years [years] x 12 [months/year] x 4 [weeks/month] x average work days per week [days/week] x average work hours per day [hours/day]. It is natural to assume that long work hours would increase the probability of becoming involved in accidents. We added new variables representing whether a worker has seen someone being punished for rule violation and/or injured by occupational accidents: *SAW_VIO_PENALTY* and *SAW_ACCIDENT*, respectively. Workers who have had such experiences may learn from these bad examples and have incentive to become more cautious in the face of possible occupational accidents. *DISLIKE* and *STRESS* will be used as explanatory variables in order to examine whether mental conditions influence accident involvement risk.

Workers' proneness to accidents is necessary information in the statistical analysis, to avoid the problem of selection bias. We adopted the score on the Cognitive Failures Questionnaire as our index of accident proneness.

CFQ: A respondent's score on the Cognitive Failures Questionnaire

The Cognitive Failures Questionnaire (Appendix 1) was designed to assess a person's likelihood of committing an error in the completion of an everyday task (Wallace et al., 2002). The questionnaire was originally developed by Broadbent et al. (1982), and has been used as an index of accident proneness. In the context of traffic accidents, for example, young men with a history of such accidents also reported higher rates of common mental errors, as quantified by their score on the Cognitive Failures Questionnaire, than a similar group of accident-free peers (Larson & Merritt, 1991). In a study analyzing the data of 2,379 American Navy recruits, the scores on the Cognitive Failures Questionnaire of individuals who had been cited for traffic accidents, hospitalized following injuries (not for illness), or injured by falling or jumping from a high place, were higher than the scores of those who had not (Larson et al., 1997). We translated the questionnaire into Japanese and administered it to respondents.

The respondents were asked 25 questions related to the frequency of lapses in three areas: perception, memory, and motor function (e.g., "Do you read something and find you haven't been thinking about it and must read it again"). The respondents answered the questions using a five-point scale: Very often = 1, Quite often = 2, Occasionally = 3, Very rarely = 4, Never = 5. Thus, the maximum and minimum score was 125 and 25, respectively. The lower the respondent's *CFQ*, the more accident prone he/she would be.

In our statistical analysis, we employed *CFQ* as an independent variable. *CFQ* may change over time, perhaps due to aging; but we held it to be stable for at least five years, and this is the reason why the occupational accident information was limited to the last five years.

2-2-4 Work type

It is natural to assume that workers engaged in more dangerous work are more likely to be involved in occupational accidents. In order to control this effect, we employ dummy variables representing the work type of a worker in our statistical model. The work types are as follows:

HIGH : If a respondent is engaged in high-elevation work, *HIGH* = 1; if not, *HIGH* = 0.

WEIGHT : If a respondent often handles heavy weights in his/her work, *WEIGHT* = 1; if not, *WEIGHT* = 0.

VEHICLE : If a respondent often drives a vehicle in his/her work, *VEHICLE* = 1; if not, *VEHICLE* = 0.

CAUGHT_IN : If a respondent faces the possibility of being caught in or crushed by equipment in his/her workplace, *CAUGHT_IN* = 1; if not, *CAUGHT_IN* = 0.

FALLING : If heavy weights can fall in his/her workplace, *FALLING* = 1; if not, *FALLING* = 0.

ELECTRIFICATION : If high voltage equipment is used in his/her workplace, *ELECTRIFICATION* = 1; if not, *ELECTRIFICATION* = 0.

CHEMICAL : If hazardous chemicals are used in his/her workplace, *CHEMICAL* = 1; if not, *CHEMICAL* = 0.

In Japan, 70％ of occupational accidents occur in these types of workplaces. Thus, in addition, we asked respondents which industry they belonged to.

2-2-5 Firm characteristics

VIOLATION : If rule violations are widespread in a respondent's workplace, *VIOLATION* = 1; if not, *VIOLATION* = 0.

WORKER_SHORTAGE : If a respondent's workplace often runs short of workers, *WORKER_SHORTAGE* = 1; if not, *WORKER_SHORTAGE* = 0.

Rule violation is considered to be one of the causes of occupational accidents (Reason, 1997)[5]. In general, company's rules are made to enhance the productivity of the firm and protect employees

5 Generally, rule violation includes violations against government rules as well. However, here we focus specifically on worker violations against their company's safety rules.

from accidents. Therefore, accidents tend to take place at firms where rules are violated. We asked respondents whether they and/or their fellow workers tend to violate the rules of the firm at their workplace, and used this information to examine the effect of rule violation on accident occurrence frequency. Earlier empirical studies did not take this effect into account; thus, this is one of our study's contributions to the literature. In addition, if a firm has a worker shortage, workers in the firm would be unusually busy, and therefore less likely to be able to expend proper time and effort in the promotion of safety.

Firms typically employ safety measures, such as education, penalties for violation of rules, rewards for no-accidents, patrols by safety managers, etc. We are interested in what sorts of safety measures are effective in reducing occupational accidents.

SAFETY_TRAINING : If a respondent's firm has in-house training programs in occupational safety, *SAFETY_TRAINING* = 1; if not, *SAFETY_TRAINING* = 0.

AC_PENALTY : If a respondent's firm has rules penalizing workers who have accidents, *AC_PENALTY* = 1; if not, *AC_PENALTY* = 0.

NO_AC_REWARD : If a respondent's firm has rules rewarding workers who avoid accidents for a certain period, *NO_AC_REWARD* = 1; if not, *NO_AC_REWARD* = 0.

PATROL : If safety managers in a respondent's firm routinely conduct patrols around their workplace, *PATROL* = 1; if not, *PATROL* = 0.

OSHMS : If a respondent's firm introduces an occupational safety and health management system, *OSHMS* = 1; if not, *OSHMS* = 0.

Among these, *AC_PENALTY*, *NO_AC_REWARD*, and *PATROL* are interpreted as "incentive schemes;" the penalties give workers the incentive not to work unsafely, while the rewards give workers the incentive to work safely. If managers routinely patrol the workplace, workers are induced to work more safely, because such patrols would increase the probability that rule violations would be discovered by managers.

3 Statistical model

We are interested in conditional variations in workers' occupational accident involvement frequency. Therefore, *ACCIDENT_FREQ* is the dependent variable in our study. As described in

Section 2-2-1, *ACCIDENT_FREQ* is expressed by discrete count data using zero or positive integers. It is inappropriate to analyze these count data using ordinary least squares, for example, and there is need for a unified and justified approach to the use of appropriate statistical models for the data (Ullah et al., 2010).

A common statistical model for dealing with discrete count data is the Poisson regression model, which is well suited to analyzing accident-count processes, and has achieved widespread use in modeling events or rates, especially when there are few incidents and hence many observed zeros (Mwalili et al., 2008; Shankar et al., 1997; Ullah et al., 2010). The Poisson distribution is defined as follows:

$$f(y) = \frac{e^{-\lambda}\lambda^{y}}{y!} \qquad \lambda > 0, y = 0, 1, 2, \ldots$$

where $f(y)$ is the probability of y occurrences in an interval. $\lambda > 0$ is the mean of this distribution; and in a Poisson distribution, the mean is equal to its variance: $\mathrm{E}(y) = \mathrm{Var}(y) = \lambda$.

In this study, *ACCIDENT_FREQ*$_i$ (in order to express the formulae succinctly, $y_i \equiv$ *ACCIDENT_FREQ*$_i$ in this section) denotes the number of occupational accidents experienced by worker *i* within a given interval of time (5 years). In the Poisson regression model (P model), the conditional distribution of y_i is assumed to be determined by worker i's covariates $\boldsymbol{x}_i$, and the parameter of the Poisson distribution λ_i is modeled as $\lambda_i = \exp(\boldsymbol{x}_i'\beta)$ where β represents the parameters to be estimated[6]. The Poisson regression model is then expressed as follows:

$$f(y_i|\boldsymbol{x}_i'\beta) = \frac{\exp\left(-\exp(\boldsymbol{x}_i'\beta)\right)\exp(y_i\boldsymbol{x}_i'\beta)}{y_i!} \qquad y_i = 0, 1, 2, \ldots$$

The maximum likelihood estimation (MLE) method was used to estimate the β parameters and their corresponding standard errors. The MLE is preferable because its estimator has the properties of consistency, asymptotic normality and minimum variance for large samples. The log likelihood function of this model is expressed below. The vector of parameters β was estimated in such a way

[6] $\boldsymbol{x}_i$ is a column vector of worker i's covariates, and $\boldsymbol{x}'_i$ is its transposition. β is a column vector of parameters.

as to maximize the log likelihood function.

$$\log L(\beta; y, \boldsymbol{x}) = \sum_{i=1}^{n} [y_i \boldsymbol{x}_i' \beta - \exp(\boldsymbol{x}_i'\beta) - \ln y_i!]$$

Although the Poisson model is widely used, the restriction on the model, that the mean and variance are equivalent, is often violated in actual count data. The negative binomial model (NB model) is a more flexible model for dealing with the above problem. The negative binomial model is expressed as follows:

$$f(y = j) = \frac{\Gamma(j+k)}{\Gamma(j+1)\Gamma(k)} \left(\frac{\mu}{\mu+k}\right)^j \left(\frac{k}{\mu+k}\right)^k \quad \mu, k > 0, j = 0, 1, 2, \ldots$$

where μ is the average number of accidents in a given time interval for each worker i , and k represents the degree of over-dispersion. Setting $\mu_i = \exp(\boldsymbol{x}_i'\beta)$, as in the case of the Poisson regression model, we generate the following regression model and its log likelihood function:

$$f(y_i | \boldsymbol{x}_i'\beta, k) = \frac{\Gamma(y_i+k)}{\Gamma(y_i+1)\Gamma(k)} \left(\frac{\exp(\boldsymbol{x}_i'\beta)}{\exp(\boldsymbol{x}_i'\beta)+k}\right)^{y_i} \left(\frac{k}{\exp(\boldsymbol{x}_i'\beta)+k}\right)^k \quad y_i = 0, 1, 2, \ldots$$

$$\log L(\beta, k; y, \boldsymbol{x}) = \sum_{i=1}^{n} \left[y_i \ln\left(\frac{\exp(\boldsymbol{x}_i'\beta)}{k}\right) - (y_i + k)\ln\left(1 + \frac{\exp(\boldsymbol{x}_i'\beta)}{k}\right) + \ln\Gamma(y_i + k) - \ln(y_i!) - \ln\Gamma(k) \right]$$

In this model, the variance of y_i is $\exp(\boldsymbol{x}_i'\beta)(1 + \exp(\boldsymbol{x}_i'\beta)/k)$, and hence increasing values of k correspond to decreasing levels of dispersion. For $k \to \infty$, the model converges on the Poisson model. When k is positive, the variance of the NB model is larger than the mean, and the model can be applied to data with over-dispersion. To test whether the data over-disperse, we compute a regression analysis as follows:

$$\frac{(y_i - \hat{\lambda}_i)^2 - y_i}{\hat{\lambda}_i} = \frac{1}{k}\hat{\lambda}_i + u_i$$

where $\hat{\lambda}_i = \exp(\boldsymbol{x}_i'\hat{\beta})$ is worker i's predicted mean of Poisson distribution calculated using the estimated coefficients of the Poisson regression. u_i is an error term. If the null hypothesis H_0: $1/k = 0$ is rejected, the NB model is judged to be appropriate. On the other hand, if H_0 is not rejected, the Poisson model is judged to be appropriate. In the next section, we conduct the over-dispersion test and discuss the factors influencing occupational accident involvement risk on the basis of the selected model (Poisson or NB model).

4 Results and discussions

4-1 Descriptive statistics

A total of 3,317 respondents answered the questionnaire. However, we removed 435 respondents from the sample pool because their answers were improper. Therefore, the effective number of samples was 2,882. The response rate was 12%.

The number of workers who had been involved in occupational accidents in the last 5 years was 119 out of 2,882, for an accident rate of 4%. As noted in Section 1, the actual accident rate in Japan was 0.23% in 2008; thus, the accident rate suggested by our data would appear to be unusually high. This discrepancy, however, is simply owing to differences in the definition of an accident. In our questionnaire, an accident was defined as a mishap in which a worker was injured enough that evaluation and treatment at a hospital were required, while for the MHLW (2010) an accident was defined as a mishap requiring an absence from work of more than four days on the part of the worker involved. If we had defined an accident as the MHLW (2010) did, the number of accidents would be too few for statistical analysis, and this is the reason for our particular definition of an accident. In our sample, no injured workers were absent from work for more than 4 days; 9 injured workers were absent from work for at least 1 day but not more than 3 days; and the remaining 110 injured workers were not required to be absent from work. The percentage of total respondents who were absent from work for at least 1 day, but not more than 3 days, as a result of an occupational accident, was 0.3%; and this figure differs only slightly from the MLHW accident rate of 0.23% (2010).

Descriptive statistics of the variables are shown in Table 1. According to our data, FWs and PWs differed in almost all aspects. The accident rate of FWs was slightly higher than that of PWs, though the difference was not statistically significant. PW's work experience, percentage of male workers, total work hours in the last five years, and income were all higher than those of FWs. This is within the expected range of difference between FWs and PWs. The proportion of workers who do not like their job was higher in the case of PWs. On the other hand, the proportion of workers who feel stress about their job was higher in FWs. "Stress" may reflect not only the work itself but also the wage level or job insecurity. The proportion of workers who have seen someone being punished for rule violation was higher in PWs; and the same held for the proportion of workers who have seen someone being injured in an occupational accident. The mean *CFQ* of FWs was lower than that of PWs; and this means that, on average, FWs in our database are more accident-prone than PWs, and *CFQ* must be included as an explanatory variable to rule out selection bias. Regarding work type, PWs tended to work in more dangerous situations. Firm characteristics were not significantly different between FWs and PWs. The results of safety measures taken by firms, on the other hand, are interesting. Table 1 shows that, with respect to all the relevant safety measurements, the proportion who answered that their workplace took safety measures was higher for PWs. Thus, the workplaces to which FWs belong tend not to take safety measures, in comparison to those of PWs, at least in our data.

Table 1 Descriptive statistics -- comparison of the average of variables between FWs and PWs

Category	Variable	FWs	PWs	Total
Accident	*ACCIDENT_FREQ*	0.05 (0.22)	0.04 (0.22)	0.04 (0.22)
Individual characteristics	*EXPERIENCE* **	55.49 (57.86)	107.56 (103.28)	87.65 (92.23)
	AGE	41.14 (10.55)	40.58 (9.95)	40.79 (10.19)
	GENDER **	0.26 (0.44)	0.60 (0.49)	0.47 (0.50)
	WORK_HOURS **	5.72 (4.39)	11.53 (5.62)	9.31 (5.91)
	CFQ **	90.31 (14.07)	91.70 (14.91)	91.17 (14.61)
	DISLIKE **	0.11 (0.31)	0.16 (0.37)	0.14 (0.35)
	INCOME **	187.43 (120.30)	551.99 (314.01)	412.60 (312.76)
	SAW_VIO_PENALTY **	0.05 (0.21)	0.11 (0.31)	0.08 (0.28)
	SAW_ACCIDENT **	0.09 (0.29)	0.13 (0.33)	0.11 (0.32)
	STRESS **	0.34 (0.47)	0.29 (0.45)	0.31 (0.46)
Work type	*HIGH*	0.02 (0.13)	0.02 (0.14)	0.02 (0.14)
	WEIGHT **	0.13 (0.33)	0.07 (0.25)	0.09 (0.29)
	VEHICLE **	0.04 (0.18)	0.07 (0.26)	0.06 (0.23)
	CAUGHT_IN	0.02 (0.15)	0.03 (0.16)	0.02 (0.16)
	FALLING **	0.01 (0.11)	0.03 (0.16)	0.02 (0.14)
	ELECTRIFICATION **	0.01 (0.12)	0.07 (0.25)	0.05 (0.21)
	CHEMICAL **	0.02 (0.13)	0.05 (0.21)	0.04 (0.19)
Firm characteristics	*VIOLATION*	0.03 (0.18)	0.04 (0.20)	0.04 (0.19)
	WORKER_SHORTAGE	0.11 (0.31)	0.11 (0.31)	0.11 (0.31)
Safety measures taken by firms	*SAFETY_TRAINING* **	0.09 (0.29)	0.13 (0.34)	0.12 (0.32)
	AC_PENALTY **	0.21 (0.41)	0.30 (0.46)	0.27 (0.44)
	NO_AC_REWARD **	0.03 (0.17)	0.13 (0.34)	0.09 (0.29)
	PATROL **	0.17 (0.38)	0.37 (0.48)	0.29 (0.46)
	OHSM **	0.08 (0.26)	0.21 (0.41)	0.16 (0.36)
NOB		1,102	1,780	2,882

Standard errors in parentheses. *10% significance. **5% significance.

4-2 Count data analysis

The results of the count data analysis are shown in Table 2 and Table 3. The estimation results are shown by industry (1st and 2nd columns of Table 2: pooled data; 3rd and 4th columns of Table 2: manufacturing; 1st and 2nd columns of Table 3: construction; 3rd and 4th columns of Table 3: other industries).

Table 2 Estimated coefficients (dependent variable: *ACCIDENT_FREQ*)

	Pooled data		Manufacturing	
	Base model (NB)	Full model (NB)	Base model (NB)	Full model (NB)
Constant	-5.047 (0.495) **	-4.459 (0.727) **	-4.913 (0.780) **	-5.272 (1.193) **
FW	0.417 (0.236) *	0.227 (0.263)	0.656 (0.396) *	0.345 (0.436)
EXPERIENCE	-0.001 (0.001)	-0.001 (0.001)	-0.005 (0.002) **	-0.005 (0.002) **
AGE	0.019 (0.011) *	0.027 (0.011) **	0.024 (0.017)	0.037 (0.018) **
GENDER	-0.008 (0.210)	0.043 (0.224)	-0.026 (0.335)	0.124 (0.354)
WORK_HOURS	0.085 (0.020) **	0.083 (0.020) **	0.080 (0.033) **	0.087 (0.035) **
Hazardous task				
HIGH	-0.107 (0.598)	-0.077 (0.597)	1.117 (0.786)	1.060 (0.789)
WEIGHT	0.934 (0.258) **	0.719 (0.267) **	0.564 (0.411)	0.338 (0.433)
VEHICLE	0.731 (0.284) *	0.522 (0.292) *	1.323 (0.441) **	1.129 (0.452) **
CAUGHT_IN	0.650 (0.413)	0.687 (0.415) *	0.125 (0.576)	-0.069 (0.589)
FALLING	-0.311 (0.584)	-0.296 (0.594)	x	x
ELECTRIFICATION	0.237 (0.397)	0.255 (0.393)	0.240 (0.493)	0.250 (0.488)
CHEMICAL	-0.263 (0.507)	-0.338 (0.522)	-0.086 (0.552)	-0.125 (0.571)
Individual characteristics				
CFQ	x	-0.008 (0.006)	x	0.004 (0.010)
DISLIKE	x	0.307 (0.263)	x	0.130 (0.424)
INCOME	x	-0.001 (0.000)	x	-0.001 (0.001)
SAW_VIO_PENALTY	x	0.787 (0.278) **	x	0.314 (0.499)
SAW_ACCIDENT	x	0.363 (0.250)	x	0.283 (0.382)
STRESS	x	-0.083 (0.211)	x	-0.249 (0.339)
Firm characteristics				
VIOLATION	x	0.943 (0.352) **	x	0.862 (0.533)
LABOR_SHORTAGE	x	-0.193 (0.300)	x	0.028 (0.449)
Safety measures taken by firms				
SAFETY_TRAINING	x	0.049 (0.303)	x	0.294 (0.462)
AC_PENALTY	x	0.291 (0.225)	x	0.398 (0.351)
NO_AC_REWARD	x	0.017 (0.346)	x	-0.144 (0.550)
PATROL	x	-0.466 (0.257) *	x	-0.391 (0.363)
OHSM	x	-0.523 (0.349)	x	-0.332 (0.463)
Log likelihood	-503.410	-487.434	-206.451	-201.213
AIC	1039.8	1028.9	438.9	454.43
NOB	2,882	2,882	1,136	1,136

Standard errors in parentheses. *10% significance. **5% significance.

Table 3 Estimated coefficients (*cont.*)

	Construction		Other industries	
	Base model (P)	Full model (P)	Base model (P)	Full model (P)
Constant	-3.070 (1.818) *	1.847 (3.932)	-5.725 (0.691) **	-4.765 (1.009) **
FW	-0.595 (1.312)	-1.631 (1.994)	0.530 (0.323) *	0.408 (0.375)
EXPERIENCE	0.005 (0.004)	0.007 (0.006)	0.000 (0.002)	-0.001 (0.002)
AGE	-0.016 (0.047)	0.025 (0.079)	0.023 (0.014)	0.030 (0.015) **
GENDER	-0.419 (0.806)	0.588(1.428)	0.118 (0.287)	0.012 (0.318)
WORK_HOURS	-0.034 (0.072)	-0.164 (0.128)	0.106 (0.026) **	0.108 (0.027) **
Hazardous task				
HIGH	-0.490 (1.489)	0.653 (1.803)	-0.839 (1.166)	-1.272 (1.455)
WEIGHT	-1.124 (1.249)	-2.620 (2.084)	1.185 (0.320) **	0.974 (0.342) **
VEHICLE	-0.672 (1.312)	-0.200 (1.763)	0.410 (0.381)	0.369 (0.424)
CAUGHT_IN	3.974 (1.183) **	6.581 (2.498) **	0.522 (1.048)	0.801 (1.067)
FALLING	2.115 (0.916) **	2.421 (1.212) **	-0.052 (1.162)	-0.593 (1.478)
ELECTRIFICATION	-0.181 (1.216)	-1.376 (2.154)	0.345 (1.067)	0.999 (1.095)
CHEMICAL	x	x	x	x
Individual characteristics				
CFQ	x	-0.089 (0.041) **	x	-0.011 (0.009)
DISLIKE	x	0.421 (1.093)	x	0.433 (0.367)
INCOME	x	-0.001 (0.003)	x	-0.000 (0.001)
SAW_VIO_PENALTY	x	2.031 (1.154) *	x	0.912 (0.378) **
SAW_ACCIDENT	x	1.009 (1.033)	x	0.527 (0.353)
STRESS	x	1.526 (0.908) *	x	-0.271 (0.306)
Firm characteristics				
VIOLATION	x	4.631 (2.171) **	x	1.088 (0.494) **
LABOR_SHORTAGE	x	-22.46 (2.542e+03)	x	-0.223 (0.404)
Safety measures taken by firms				
SAFETY_TRAINING	x	-18.55 (4.460e+03)	x	-0.167 (0.412)
AC_PENALTY	x	1.897 (1.168)	x	0.092 (0.308)
NO_AC_REWARD	x	-0.117 (1.541)	x	-0.283 (0.528)
PATROL	x	-0.477 (0.995)	x	-0.371 (0.419)
OHSM	x	-0.684 (1.453)	x	-1.021 (0.654)
Log likelihood	-39.404	-26.450	-241.271	-230.344
AIC	102.8	102.9	506.5	510.7
NOB	237	237	1,509	1,509

Standard errors in parentheses. *10% significance. **5% significance.

Figure 2 shows a comparison between observed and fitted numeric distributions of occupational accidents, and demonstrates that the estimation model can well both predict and explain the observed data[7].

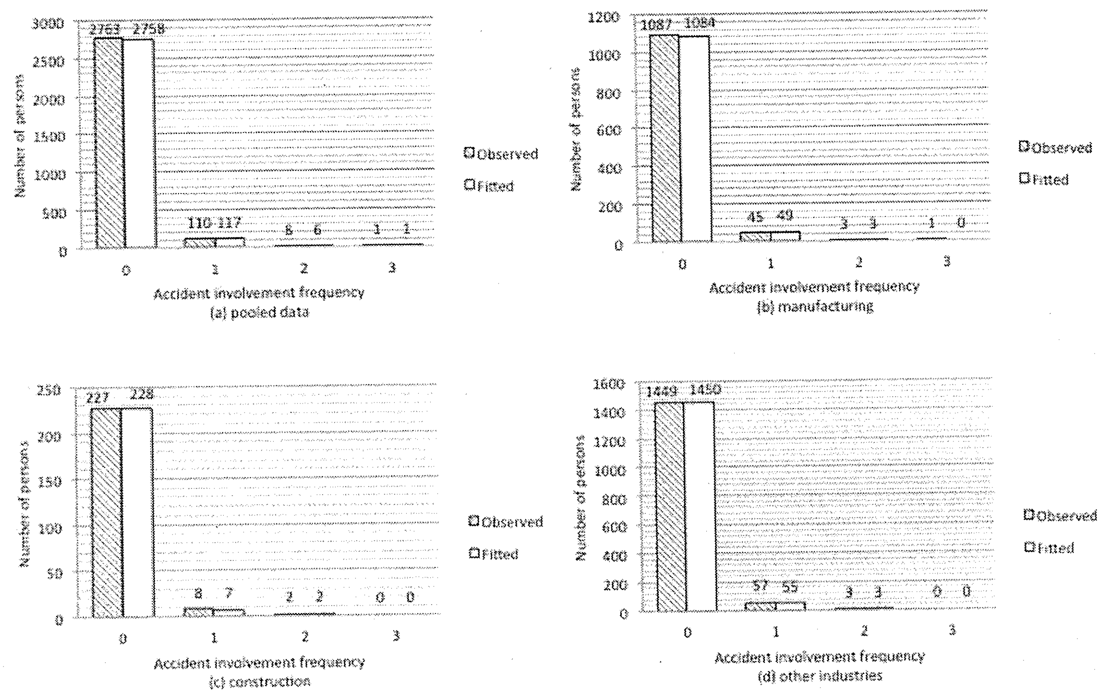

Figure 2 Observed and fitted numeric distributions of occupational accidents

First, we will discuss the estimation results based on the pooled data (1st and 2nd columns of Table 2), in order to get an overall picture of the analysis; and then discuss the industry-specific results. The 1st and 2nd columns of Table 2 show the results of the "base model" and "full model," respectively. In the parentheses following the "base model" and "full model" labels, the statistical model chosen on the basis of the over-dispersion test is indicated (P or NB). The independent variables of the base model were *FW*, *EXPERIENCE*, *AGE*, *GENDER*, *WORK_HOURS*, and variables representing the work type. In the full model, variables representing individual characteristics and firm characteristics were added to the base model, for the reasons described in Sections 2-2-3 and 2-2-5.

7 Articles discussing "zero inflated" count data analysis in the context of accidents include Shankar et al. (1997), Mwalili et al. (2008), and Ullah et al. (2010). However, as Figure 2 clearly shows, zero inflation is not observed in our data.

In the base model, the estimated coefficient for *FW* is positive and significant. This estimation result seems to suggest that FWs are more involved in occupational accidents. We will reexamine this issue in the discussion of the full model and the industry-specific analysis. The estimated coefficient for *AGE* is also positive and significant. Although old workers generally have more work experience than young workers, this effect is controlled by including *EXPERIENCE* in the model; and this means that the estimated coefficient for *AGE* does not capture the effect of worker experience. It may indicate a decrease in the worker's physical ability and/or judgment through aging. The estimated coefficient for *WORK_HOURS* is positive and statistically significant. Those with long work hours have increased opportunities to be exposed to dangerous situations, and tend to be more fatigued; therefore, this is a logical result. *EXPERIENCE* is not significant, and this would appear to be due to the fact that *EXPERIENCE* and *WORK_HOURS* are correlated (correlation coefficient: 0.58). Considerable experience *per se* seems to have, if any, only a limited impact on accident involvement frequency. Previous studies may not have considered the correlation between *EXPERIENCE* and *WORK_HOURS*. Among the variables representing work type, the estimated coefficients for *WEIGHT* and *DRIVE* were positive and significant.

We turn now to the estimation results of the full model. It is important to note that the estimated coefficient for *FW* is no longer significant in the full model. The observed impact of being an FW *per se*, on the occupational accident involvement risk in the base model, disappeared with the inclusion of the variables on individual characteristics and firm characteristics in the full model. Thus, the effect detected in the base model would appear to be spurious. The estimated coefficients for the other variables also included in the base model maintained their sign and significance. The estimated coefficient for *CAUGHT_IN* became significant.

The estimated coefficient for *CFQ* was not significant. Thus, workers' accident-proneness would appear to have no impact on their occupational accident involvement risk; and this means there is no selection bias based on the estimation results using the pooled data.

The estimated coefficient for *VIOLATION* was positive and significant. Company's rules are established not merely to enhance productivity but also to protect workers from accidents; and this would suggest that rule violation increases the accident probability. The result shown in Table 2 would appear to support this relationship. However, it is difficult to make workers obey rules, and rule obeyance often involves costs, both pecuniary and non-pecuniary. Typically, workers must follow more steps and put more time and effort into doing their job, so as not to break the company's rules. Therefore, workers tend to have incentive to break rules in order to reduce their time, effort and/or opportunity costs. Thus, an incentive scheme which can prevent workers from breaking the rules will be effective in accident reduction, and the design methodology of such an incentive scheme needs to be explored.

It is important to note that the estimated coefficient for *SAW_VIO_PENALTY*, which is one of the individual characteristics, was positive and statistically significant. We expected that this would be negative because of the "bad example effect" described in Section 2-2-3. But this was not supported by our data. One possible interpretation of this result is that the penalties established by the companies of our respondents were too light, and thus did not work effectively as an incentive for workers not to violate the rules. Therefore, these light penalties might have sent the wrong message to workers; for example, 'as long as the penalty is paid, it is alright to violate the rules,' or 'it is more beneficial to violate the rules than to obey them, because the penalties for violation are so light.' The point of this interpretation is that an incentive scheme might, in fact, have the opposite effect from the safety manager's intention and expectation. *DISLIKE* and *STRESS*, representing mental conditions, were not significant in terms of accident involvement frequency.

It is also interesting that the coefficient for *SAW_ACCIDENT* was not significant. In Japan (and perhaps in other countries), employees are typically shown pictures or movies depicting scenes of serious occupational accidents, as part of safety training. The intention of safety managers, here, is to make employees understand the context, and fear the consequences, of accidents, and thereby take care in their work. However, our estimation results suggest that, contrary to expectations perhaps, such activities would not be effective, because even workers who watched the 'real' accidents did not necessarily become safer workers after witnessing the accidents.

Among the variables representing safety measures taken by firms, only the coefficient for *PATROL* was estimated as significant, with a negative sign as expected. Safety manager patrols would provide incentive for workers to work more safely. Although the coefficient for *OHSM* is not significant, its p-value is small ($p = 0.133$), suggesting that the introduction of an occupational health and safety management system would have some efficacy in accident reduction. It is interesting that the coefficient of *SAFETY_TRAINING* was not significant. Some sort of safety training or education of workers is common, and often presented as a safety measure in accident reports or databases. However, based on our results, such training or education seems not necessarily to be effective.

Manufacturing (3rd and 4th columns of Table 2) We will discuss the industry-specific estimation results below. Here, the estimation results for manufacturing will be examined. *FALLING* was not included as an independent variable because no manufacturing workers in our data answered that the possible fall of heavy weights was an issue in their workplace. Although the estimated coefficient for *FW* is positive and significant in the base model, *FW* becomes insignificant in the full model, a change reflected also in the pooled data. The estimated coefficient for *EXPERIENCE* was negative and significant. Significant work experience would lessen the accident involvement risk. Typically, workers operate machines in the manufacturing sector. Familiarity with the operation of such machines usually means an increase in the relevant operational skills, and this may lead to accident reduction. Furthermore, inattention or a false sense of security resulting from considerable experience does not dominate this increased-skills effect in our data. The estimated coefficient for *VIOLATION* was almost significant ($p = 0.1061$), suggesting that this factor would have a certain degree of impact on accident involvement frequency in the manufacturing sector. *SAW_VIO_PENALTY* was not significant for manufacturing workers.

Construction (1st and 2nd columns of Table 3) *CHEMICAL* was not included as an independent variable, because no workers in the construction sector in our data answered that hazardous chemicals were used in their workplaces. The estimation results here are different from those of manufacturing. No variables beyond those representing certain types of work were significant in the base model. In the full model, it is notable that the estimated coefficient for *CFQ* was negative and significant. As explained in Section 2-2-3, the lower the respondent's *CFQ*, the more accident prone he/she would be. Therefore, construction workers who tend to suffer from cognitive failures also tend to be involved in occupational accidents. However, remember that *FW* is not significant in the base model. Therefore, it is not true that *FW* was estimated as significant under the influence of selection bias. Finally, the estimated coefficient for *VIOLATION* and *SAW_VIO_PENALTY* was positive and significant, as in the case of the pooled data.

Other industries[8] (3rd and 4th columns of Table 3) *CHEMICAL* was excluded from the statistical model for the same reason as in the analysis respecting construction workers. The estimation results of the other industries reflected a mixture of the results for manufacturing and construction. The significance of *AGE* and *WORK_HOURS*, here, was similar to the results for manufacturing workers, and the significance of *SAW_VIO_PENALTY* and *VIOLATION* was similar to the results for construction workers. Although the coefficient for *FW* was positive and significant in the base model, it was no longer significant in the full model. On the other hand, the coefficient for *VIOLATION* was again positive and significant. Thus, according to our data, rule violation has a positive relationship with accident occurrence in all industries, and this effect seems to be universal, regardless of the business sphere. Among the individual characteristics, *SAW_VIO_PENALTY* was estimated as positive and significant.

What means are effective, then, in decreasing occupational accidents involving FWs, on the basis of our statistical results? Both our pooled data and industry-specific data suggest that the mere fact of being an FW does not increase the risk of occupational accident involvement, and thus that there is no "pure contractual effect." Therefore, rehiring FWs as PWs would not contribute to accident reduction, at least in Japan. The safety measures taken by firms (e.g., safety patrols by managers, and the introduction of an occupational health and safety management system) seem to have an impact on accident reduction, as shown in the estimation results of count data analysis (Table 2), but such safety measures tend to be less prevalent in workplaces involving FWs than in those involving PWs, as is clearly demonstrated by the descriptive statistics (Table 1). These results may suggest that FWs tend to be more involved in occupational accidents because the safety measures in their workplaces are not sufficient, relative to those in PWs' workplaces. In addition, the insignificance of the estimated coefficient for *CFQ* and *SAFETY_TRAINING* suggests that an individual's specific ability is not particularly important in occupational safety. Therefore, safety measures that aim to develop "organizational effectiveness" regarding safety (e.g., safety patrols or the introduction of an OHSMS) would be more effective in occupational accident reduction than those that aim to develop "personal ability" (e.g., education or safety training)—contrary to the conclusions of many accident reports, at least with regard to the Japanese workplace.

8 Out of the 1,509 samples in "other industries," there were 408 samples in service, 312 in others, 278 in financial businesses other than securities, 113 in retailing, 105 in warehousing, 91 in communication services, 36 in securities, 34 in bus and train services, 33 in the electricity supply industry, 26 in land transportation, 20 in trading companies, 15 in real estate, 13 in gas companies, 13 in air transportation, 8 in marine transportation, 3 in fisheries, and 1 in mining. The top 5 industries account for 80% of "other industries."

5　Conclusions

We analyzed the data collected by an Internet survey, to determine which factors influence the accident involvement risk of workers. Our study particularly focused on the effect of employment status (flexible employment or permanent employment) on occupational accident risk. We attempted to exclude the effects of a host of confounding factors, the most important of which is the score on the Cognitive Failures Questionnaire, which quantifies a given respondent's accident proneness. Our findings may be summarized as follows. (1) A pure contractual effect was not detected in our data. This means that changing a worker's employment status from FW to PW would not be effective as an accident reduction measure. (2) Our data suggest that, typically, a worker's job experience does not significantly influence their accident involvement frequency, though existing studies suggest that the greater the work experience, the lower the probability of occupational accident involvement. (3) The score on the Cognitive Failures Questionnaire, which is an index of accident proneness, does not appear to have any relation to accident involvement risk, except in the case of construction workers. (4) *SAW_VIO_PENALTY* is positively significant, but *SAW_ACCIDENT* is not significant; and both results suggest that there is no "bad example effect." This means that safety education may be less effective than often thought as an accident reduction measure. (5) *VIOLATION* is (nearly) significant in all industries. Thus, an incentive scheme that encourages workers to follow safety rules will tend be effective in accident reduction. However, the specific design methodology for such an incentive scheme needs to be explored. (6) Among the accident reduction measures taken by firms, safety manager patrols, and the introduction of an occupational health and safety management system, would have an impact on occupational accident reduction. Although other variables representing safety measures taken by firms were not significant, this does not necessarily mean that incentive schemes like penalties and rewards are ineffective as accident reduction measures. Their apparent ineffectiveness may, for example, be owing to the establishment of ineffective penalty or reward levels; and thus, if these levels were properly set, the related incentive schemes may be effective as accident reduction measures.

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