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**Série Scientifique**
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**97s-24**

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Montréal
Mai 1997

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**ISSN 1198-8177**

# Incentive Effects of Public Insurance Programs on the Occurrence and the Composition of Workplace Injuries*

*Denis Bolduc*†, *Bernard Fortin*‡, *France Labrecque*§, *Paul Lanoie*¶

## Résumé / Abstract

Cet article présente des résultats empiriques selon lesquels l'assurance contre les accidents du travail (AA) et l'assurance-chômage (AC) n'influencent pas uniquement l'incidence des accidents du travail, mais aussi la composition des accidents rapportés. Le cadre théorique prédit que, selon les hypothèses plausibles, une hausse du taux de remplacement du salaire par l'AA (ou baisse du taux de remplacement du salaire par l'AC) conduit à une augmentation plus élevée de la probabilité de déclarer une lésion professionnelle difficile à diagnostiquer qu'une lésion facile à diagnostiquer. Aux fins d'estimations, on utilise des données longitudinales mensuelles sur plus de 9800 travailleurs œuvrant dans le secteur de la construction au Québec entre 1977 et 1986. Ces données proviennent d'un jumelage de données administratives de la Commission de la construction du Québec et de la Commission de la santé et de la sécurité du travail. Les paramèters du modèle sont estimés à l'aide d'un modèle probit potytomique à trois alternatives avec effets individuels aléatoires. Les résultats confirment les prédictions du modèle théorique. En particulier,

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Financial support from the Fonds FCAR is gratefully acknowledged. We are grateful to Michael Hoy, Jean-François Wen and participants at the DELTA, the LAMIA and the CEREQ for comments on earlier version, and to Marcel Dagenais, Georges Dionne and Guy Lacroix for useful discussions. Pierre Fortin and Denis Guindon provided us with information needed for the construction of the wage replacement rates under the unemployment insurance and workers' compensation systems in place in the Province of Québec. We thank the members of the Groupe interdisciplinaire de recherche sur l'organisation, la santé et la sécurité au travail (GIROSST) of Université Laval for providing us with the data and for their helpful advice.

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l'élasticité de la probabilité d'accidents par rapport au taux de remplacement de l'AA varie entre 0,83 et 1,45 dans le cas de lésions difficiles à diagnostiquer, et entre 0,72 et 1,03 dans le cas de lésions faciles à diagnostiquer (pour la période entre 1979 et 1986). En outre, la probabiblité de déclarer un accident difficile à diagnostiquer s'accroît durant la saison d'hiver (i.e. la saison où le taux de chômage dans le secteur de la construction est le plus élevé).

*This paper provides evidence that workers' compensation (WC) and unemployment insurance (UI) could affect not only the occurence of workplace accident claims, but also the composition of these reported accidents. Our theoretical framework predicts that, under plausible assumptions, an increase in the wage replacement ration under WC (or a decrease in the UI wage replacement ratio) leads to a larger increase in the probability of reporting a difficult-to-diagnose injury than in the probability of reporting an easy-to-diagnose injury. Panel data on 9800 workers in the Québec construction industry over each month of the period 1977-1986, combining administrative data from the Québec Construction Board and the Québec Workers' Compensation Board, were used for the estimations. The parameters of the model are estimated using a three alternative MultiNomial Probit (MNP) framework with individual random effects. Our results confirm our theoretical predictions. In particular, the impact of the WC replacement ratio on the probability of accidents ranges (in terms of elasticity) from 0.83 to 1.45 for difficult-to-diagnose injuries and from 0.72 to 1.03 for easy-to-diagnose injuries (for the period 1979-1986). In ligne with this result, we also show that the probability to report a difficult-to-diagnose injury is significantly greater in winter (the dead season in the construction industry) than in other seasons.*

**Mots Clés :** Lésions professionnelles, assurance-chômage, aléa moral, probit polytomique

**Keywords :** Workers' compensation, unemployment insurance, moral hazard, multinomial probit

JEL : J28, J65

# 1 Introduction

The social cost of workplace accidents is large. In a typical year in the United States, from one-third to one-half as many working days are lost to work injuries as are lost to unemployment (see Krueger, 1988). Public or private provision of insurance against workplace accidents exists everywhere in industrial countries. Given the fact that the insurer has imperfect information on the actions of the insured and on the state of nature, these programs are the source of moral hazard problems. Thus the provision of insurance may affect the incentives of the insured to make prevention efforts or may induce him to report a more severe accident than it is the case. A number of papers provide empirical analyses of the incentive effects of workers'compensation (WC) insurance. In particular, they show that an increase in the wage replacement ratio under WC is associated with an increase in the frequency of reported accidents (*e.g.*, Krueger, 1990), or in the duration of WC claims (*e.g.*, Fortin and Lanoie, 1992 and Meyer, Viscusi and Durbin, 1995). Furthermore, recent studies provide empirical evidence that WC insurance may be used as a substitute for unemployment insurance (UI). Thus workers who are about to be laid-off may have incentives to reduce their prevention efforts or to attempt to prolong their period of absence from work due to an accident, insofar as the generosity of WC is greater than that of UI (see Fortin and Lanoie, 1992 and Fortin et al. 1994).

In this paper, we extend this literature by showing that WC insurance also affects the composition of reported occupational injuries. Indeed, increases in the WC wage replacement ratio may lead to another form of moral hazard: the reporting of injuries that did not occur or occurred off-the-job, but that are difficult to diagnose (e.g., low-back injuries). The first study that explicitly analysed the incentive to shirk is Staten and Umbeck (1982). More recently, Smith (1989) provided evidence that WC claims related to back disorders are more likely to arise on Mondays than on other weekdays, raising the concern that WC is paying the costs of some off-the-job illnesses and injuries. He argued that this could be due to the fact that, for many workers, WC compensation is more generous than off-the-job medical insurance.[1]

[1]This paper raised some controversies though. Thus Card and McCall (1994), combining administrative data on workplace injury claims with CPS data on medical insurance coverage, are not able to show that workers with lower medical coverage rates are more likely to report a Monday injury than other workers. They conjecture that the "Monday effect" may be a consequence of the return to work after a "weekend hiatus" (p.20).

Our paper innovates in several respects. First, our theoretical framework extends the present literature, which simply considers that a worker can either have an accident or not (e.g., Krueger, 1990), to the case where he can also report a false, difficult-to-diagnose, injury. As a result, three alternatives are possible for the worker: 1) he has a difficult-to-diagnose accident (true or false), 2) he has an accident with easy diagnosis, or 3) he has no accident. Based on an expected utility framework, our model predicts that, under reasonable assumptions, an increase in the wage replacement ratio under WC (or a decrease in the UI wage replacement ratio) leads to a larger increase in the probability of reporting a difficult-to-diagnose injury than in the probability of reporting an easy-to-diagnose injury.

Second, panel data on 9800 workers in the Quebec construction industry over each month of the period 1977-1986, combining administrative data from the Commission de la construction du Québec with data from the Commission de la santé et sécurité du travail (the Quebec Workers' Compensation Board), are used in the estimations. Previous authors who have studied workplace accidents frequency with individual data have used cross-section data (Krueger, 1990, Moore and Viscusi, 1990). Advantages of panel data over cross-section data are well-known (for a thorough discussion, see Baltagi, 1995). In particular, panel data allow to control for individual heterogeneity. In a study of workplace accidents frequency, there may be many variables that are individual-invariant (e.g., unobserved dexterity) or time-invariant (e.g., technological changes) that may affect accidents. Omission of these variables may lead to biases in the resulting estimates. Estimating methods using panel data can control for these individual- and time-invariant variables whereas methods based on time-series or on cross-section data cannot. Furthermore, for our purposes, the construction industry is particularly interesting given that it is one of the most dangerous sectors in terms of workplace accidents (CSST, 1982) and given that, because of climate constraints, many workers expect to be unemployed during winter time. Since WC benefits are much more generous than UI benefits in Quebec, this may lead workers to attempt to use WC as a disguised unemployment insurance.

Our empirical approach is an extension to panel data of the approach developed in Bolduc et al. (1996) and Bolduc and Ben-Akiva (1991). The parameters of the model are estimated using a three alternative MultiNomial Probit (MNP) framework with random effects. This model, refered to as a panel hybrid MNP, has an error component structure which includes individual-invariant random terms, a time- and individual-varying term and a i.i.d. Gumbel term. Many discrete choice models used in the literature can be seen as a special case of our econometric framework. In particular, the presence of the i.i.d. Gumbel component allows the standard MultiNomial Logit (MNL) model and the panel Multinomial Logit model to be nested within our approach. A panel hybrid Independent MultiNomial Probit (IMNP) formulation, consistent with the absence of correlated errors across alternatives, is also a special case of our approach.

This paper is likely to contribute to demonstrate the feasibility of the MNP framework with panel data and random effects. This formulation is particularly appropriate since ignoring the random effects and performing a standard probit analysis can lead to inconsistent estimates and misleading inference (see Guilkey and Murphy, 1993).[2]

The rest of the paper is organized as follows: Section 2 presents the theoretical model, while the data and the econometric framework are discussed in Section 3. Section 4 presents the empirical results which confirm our main prediction, *i.e.*, that an increase in the generosity of WC (and a reduction in the generosity of UI) leads to a larger increase in the probability of reporting a difficult-to-diagnose injury than an easy-to-diagnose one. Section 5 provides concluding remarks.

## 2 The model

The model presented in this section extends the one discussed in Fortin and Lanoie (1992) in two directions. First, it introduces two types of injuries (easy- and difficult-to-diagnose injuries). Second, it allows the worker to report a false, difficult-to-diagnose, injury. Following most of the litterature, the theoretical model considers only the worker's behaviour and ignores that of the employer.[3] However, the empirical model does take into account the effect of some policy changes (*e.g.* the introduction of experience rating) on the incentives of employers to influence

[2]For another application of a MNP with panel data and random effects, see Elrod and Keane (1995) who estimate detergent choice models where each household is facing eight choices over thirty periods.

[3]The model focuses on moral hazard and assumes no adverse selection. The latter assumption is justified by the fact that the proportion of workers who are insured by the WC program is close to 100% (only domestic servants and workers in the sport industry are excluded from the program).

the level of reported accidents (*e.g.* by investing in accident-preventing effort).[4]

Let us consider a worker who contemplates the possibility of reporting (with a certain cost) a false accident in order to claim WC benefits. If he decides to work instead, he must then choose the level of effort to make in order to prevent the occurrence of a workplace accident. This worker has thus a two-step optimization problem to solve. In the first step, he decides to report or not a false, difficult-to-diagnose, accident. In the second step, conditional upon choosing not to report a false accident, he chooses the optimal level of prevention effort in order to reduce the probability of (true) injuries. Under the assumption that the physician who determines the duration of the recovery period is a neutral agent of the worker[5], the duration of the recovery period compensated by WC is also a choice variable, at least for a difficult-to-diagnose injury (false or true). Following the procedure used in dynamic games, we first solve the second-step problem. The first-step one is then backwardly solved using the solution obtained for the second-step problem.

The horizon decision of the worker is defined on a period of $T$ days and the accident, if it occurs, takes place at the beginning of the period. The worker is assumed to have accumulated rights to UI benefits and can thus claim UI benefits when he is not working and not drawing WC benefits.[6] In order to reflect the situation prevailing in Quebec, it is assumed that the net UI benefit per unit of time, $r$, is less than the net WC benefit, $a$, *i.e.,* $r < a$. Conditional upon his decision not to report a false accident, the risk-averse worker's expected utility is given by:

$$EU \ = \ p^d(k)\, u^d(x^d, l^d) + p^e(k)\, u^e(x^e, l^e) + (1 - p^d(k) - p^e(k))\, u^n(x^n, l^n) - k. \tag{1}$$

In (1), indexes $d$, $e$ and $n$ correspond to the state of the nature where there is a difficult-to-diagnose accident, an easy-to-diagnose accident and no accident, respectively. The ex-post utility function $u^i(\cdot)$, for $i = d, e, n$, is a concave function of the net income $x^i$ and leisure $l^i$. The variable $k$ denotes the level of accident-preventing effort by the worker. The probability of the occurrence of an accident easy- or difficult-to-

[4]For a model that takes into account both workers' and employers' behaviour, see Lanoie (1991). Note that the large majority of studies on the impact of experience rating conclude that its effect is small or not significant on the level of reported accidents (*e.g.* see Ruser 1985 and Kniesner and Leeth 1988).

[5]In Quebec, contrary to most regions, the injured worker has the choice of the doctor.

[6]For simplicity, it is assumed that refusing or quitting jobs is not penalized in terms of UI benefits.

diagnose is a decreasing convex function of $k$, that is, $p^i = p^i(k)$, with $p^i_k < 0$ and $p^i_{kk} > 0$, for $i = e, d$.[7]

While the worker has no control on $d^e$, the period of absence compensated by WC when the injury is easy to diagnose, he has some degree of freedom (through the choice of his doctor, for example) in setting the duration of this period, in the case of a difficult-to-diagnose injury. However, this implies a cost for the worker that is increasing at an increasing rate with the period of absence, $d^d$, approved in the medical report above a lower bound, $\overline{d}$: $c = c(d^d - \overline{d})$, with $c(0) = 0$, $c' > 0$ and $c'' > 0$.[8]

In order to solve the second-step problem, one must derive the indirect utility function associated with each of the three states of nature and then, the optimal accident-preventing effort. First, conditional upon experiencing a difficult-to-diagnose injury, the worker's net income is given by: $x^d \;=\; w(T - l^d) + ad^d + r(l^d - d^d) - c(d^d - \overline{d})$, where $w$ is the worker's net wage rate, $T - l^d$ represents the number of working days and $l^d - d^d$, the period spent on UI. Assuming an interior solution (*i.e.*, $l^d > d^d > \overline{d}$), the first-order conditions imply that the net compensation for one additional day of leisure is the same, whether the individual is compensated by WC or UI benefits, that is, $a - c'(d^d - \overline{d}) = r$. Solving for $d^d$ yields $d^d = \overline{d} + \tilde{d}(a - r)$ with $\tilde{d}_{a-r} > 0$. It is easy to show that the indirect utility function is given by $v^d = v^d(w - r, y^d)$, where $y^d \;=\; rT + (a - r)\; d^d - c(d^d - \overline{d})$ is the virtual nonwage income corresponding to this state of nature. Using Roy's Identity and the envelope theorem, the marginal utility of WC and of UI benefits are respectively given by: $v^d_a \;=\; v^d_{y^d}\; d^d > 0$ and $v^d_r \;=\; v^d_{y^d}\; (l^d - d^d) > 0$. These latter equations indicate that the marginal utility of each type of benefits is given by the product of the marginal utility of income and the period spent on the corresponding insurance program.

The analysis is similar when the worker has an easy-to-diagnose injury. His net income is given by $x^e \;=\; w(T - l^e) + ad^e + r(l^e - d^e)$, where the period of recovery, $d^e$, is now an exogenous variable. The corresponding indirect utility function is given by $v^e = v^e(w - r, y^e)$ where the virtual nonwage income is given by $y^e \;=\; rT + (a - r)\; d^e$. In this case, the marginal utility of WC and of UI benefits are respectively given

[7] These probabilities may also depend on the accident-preventing efforts by the employer, but we ignore this possibility to simplify the presentation.

[8] These costs may thus reflect the resources required to find a cooperative doctor. Our approach abstracts from the risk related to the probability of control and rejection of the physician's report. This is in line with tax evasion models which suppose that tax-evasion activities are foolproof but entail real or psychic costs ( Kesselman 1989).

by: $v_a^e = v_{y^e}^e \; d^e > 0$ and $v_r^e = v_{y^e}^e \; (l^e - d^e) > 0$. Finally, in the third case, when the worker has no accident, his indirect utility function is given by $v^n = v^n(w - r, y^n)$, with $y^n = rT$. In that case, the marginal utility of UI benefits is given by: $v_r^n = v_{y^n}^n \; l^n$.

Let us now derive the optimal level of accident-preventing effort, $k$, in the second-step problem. Substituting the ex-post indirect utility functions into the definition of the expected utility function (1), $k$ is obtained by solving the following problem:

$$\begin{aligned} \max_k EU = \quad & p^d(k)\; v^d(w - r, y^d) + p^e(k)\; v^e(w - r, y^e) + \\ & (1 - p^d(k) - p^e(k))\; v^n(w - r, y^n) - k \end{aligned} \tag{2}$$

The first-order condition to this problem is:

$$p_k^d \; (v^d - v^n) + p_k^e \; (v^e - v^n) - 1 = 0, \tag{3}$$

where it is assumed that the worker prefers to have no (true) accident, that is, $v^i < v^n$ for $i = d, e$. Equation (3) can be solved to determine the optimal level of $k$ as a function of the exogenous variables. Since the probability of each type of accidents is a function of $k$, the reduced-form equation for these probabilities depends also on the exogenous variables:

$$p^d \;=\; \hat{p}^d(a, r, w) \quad \text{and} \quad p^e \;=\; \hat{p}^e(a, r, w) \tag{4}$$

Differentiating (3) and using the second-order condition, it can be shown that these functions have the following properties:

$$\begin{aligned} \hat{p}_a^i \quad &= \quad -p_k^i \; (p_k^d \; v_a^d + p_k^e \; v_a^e)/\Delta > 0 \\ \hat{p}_r^i \quad &= \quad -p_k^i \; (p_k^d \; (v_r^d - \; v_r^n) + p_k^e \; (v_r^e \; - \; v_r^n))/\Delta \\ \text{for } i \quad &= \quad d, e \quad \text{and where} \quad \Delta = (v^d - v^n)\; p_{kk}^d + (v^e - v^n) p_{kk}^e < 0 \end{aligned}$$

Therefore, the effect of an increase in WC benefits on the probability of (true) accidents is unambiguously positive, whether the accident is difficult- or easy-to-diagnose. However, without additional structure, it is not clear whether this impact is stronger on difficult-to-diagnose accidents. This issue depends on the technology relating accident-preventing efforts to the probability of each type of accidents (*i.e.*, whether $p_k^d$ is less or greater than $p_k^e$). Moreover, the effect of an increase in UI benefits, $r$, is ambiguous and critically depends on the signs of $v_r^d - \; v_r^n$ and of $v_r^e - \; v_r^n$. However, if one is ready to assume, as we will in the sequel, that the marginal utility of $r$ is smaller when there is an accident than when there is no accident, $\hat{p}_r^i$ will be negative, for $i = d, e$.

Let us now turn to the first-step problem which consists, for the worker, to choose or not to report a false accident. The solution to this problem comes from a comparison between the indirect utility associated with each alternative. The (expected) indirect utility associated with the choice not to report an accident, $V^{nf}$, is obtained by substituting the equation for the probability of each type of accident (see (4)) and the definition of the three nonwage income variables into (2). One thus obtains:

$$\begin{aligned} V^{nf} &= V^{nf}(a,r,w), \quad \text{with} \qquad (5)\\ V_a^{nf} &= p^d\ v_{y^d}^d\ d^d + p^e\ v_{y^e}^e\ d^e > 0 \quad \text{and}\\ V_r^{nf} &= p^d v_{y^d}^d (l^d - d^d) + p^e v_{y^e}^e (l^e - d^e) + (1 - p^d - p^e) v_{y^n}^n l^n > 0. \end{aligned}$$

Now, conditional upon reporting a false, difficult-to-diagnose, accident, the worker's net income is given by: $x^f = w(T - l^f) + a\ d^f + r(l^f - d^f) - c(d^f)$. In order to allow for heterogeneity in the degree of immorality aversion across workers that is observable by the worker but unobservable by the econometrician, a random term $\epsilon$, with a symmetric density function $f(\epsilon)$, is added to the utility function corresponding to this situation. Therefore, the indirect random utility function is given by: $V^f = v^n(w - r, y^f) + \epsilon$, where $y^f = rT + (a - r)\ d^f\ -\ c(d^f)$ is the virtual nonwage income and with $d^f = \tilde{d}(a - r)$. Substituting this definition into the indirect utility function, the latter can be expressed as:

$$\begin{aligned} V^f &= V^f(a,r,w) + \epsilon, \quad \text{with} \qquad (6)\\ V_a^f &= v_{y^f}^n\ d^f > 0 \text{ and } V_r^f = v_{y^f}^n (l^f - d^f) > 0. \end{aligned}$$

The introduction of a random term in (6) allows us to analyse the impact of a marginal change in WC (or UI) benefits on the probability of reporting a false accident, $p^f$. The latter corresponds to the probability that $V^f(\cdot) + \epsilon > V^{nf}(\cdot)$, *i.e.*, that $\epsilon > V^{nf}(\cdot) - V^f(\cdot)$. Therefore, it is given by the equation: $p^f = F(V^f(\cdot) - V^{nf}(\cdot))$, where $F(\cdot)$ is the cumulative function of $\epsilon$. Using (5) and (6), the reduced-form equation for $p^f$ can be written as:

$$\begin{aligned} p^f &= \hat{p}^f(a,r,w), \quad \text{with} \qquad (7)\\ \hat{p}_a^f &= f(\cdot)\ (v_{y^f}^n\ d^f - [p^d\ v_{y^d}^d\ d^d + p^e\ v_{y^e}^e\ d^e]) \quad \text{and} \qquad (8)\\ \hat{p}_r^f &= f(\cdot)\ (v_{y^f}^n (l^f - d^f) - [p^d v_{y^d}^d (l^d - d^d) +\\ &\quad p^e v_{y^e}^e (l^e - d^e) + (1 - p^d - p^e) v_{y^n}^n l^n]) \qquad (9) \end{aligned}$$

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From (8), one cannot theoretically sign the impact of an increase of WC benefits on the probability of reporting a false injury. However, a glance on the right-hand side of this equation shows that it is very likely to be positive and will be assumed so, in the sequel. The basic reason is that the expression within brackets in (8), which represents the impact of an increase in $a$ on the expected utility level when there is no false accident, is likely to be smaller than $v^n_{y^f}\ d^f$, which represents its impact on the utility level when the worker reports a false accident. First, in the latter case, an increase in WC benefits directly affects the worker's utility level while, in the former case, its effect on his expected utility level depends on the probabilities of experiencing a true accident, which are likely to be small. Second, the marginal utility of income is likely to be smaller when there is a true accident. In fact, if one assumes that the marginal utility of income and the duration of injuries are the same in each case and are respectively given by $v_y$ and $d$, one has from (8): $p^f_a = f(\cdot)\ v_y\ d\ (1 - p^d - p^e) > 0$.

Similarly, while the impact of an increase in UI benefits on the probability of reporting a false accident is theoretically ambiguous (see (9)), it is likely to be negative and will again be assumed so, in the sequel. Here, the basic reason is that, in the absence of a true accident, the duration of the period on UI is likely to be longer when the worker does not report a false accident than when he does, *i.e.*, $l^n$ is likely to be greater than $l^f - d^f$. Again, under the assumption that the marginal utility of income, the level of leisure and the duration of accidents (true or false) are the same in each situation, one obtains from (9): $p^f_r = -f(\cdot)\ v_y\ d\ (1 - p^d - p^e) < 0$.

What are the implications of our analysis on the impact of an increase of WC (or of UI) benefits on the probability of a difficult-to-diagnose injury as compared with an easy-to-diagnose injury? To answer this question, let us first derive the equation for the probability of a (true or false) difficult-to-diagnose injury $p^D$. Using (4) and (7), it is given by:

$$p^D = \hat{p}^f(a,r,w) + (1 - \hat{p}^f(a,r,w))\ \hat{p}^d(a,r,w), \quad (10)$$
$$\text{with } \hat{p}^D_i = \hat{p}^f_i + \hat{p}^d_i - \hat{p}^d_i\ p^f - \hat{p}^f_i\ p^d, \quad \text{for } i = a, r. \quad (11)$$

Equation (10) uses the fact that $p^D$ is the sum of the probability of a false injury and of the unconditional probability of a true, difficult-to-diagnose, injury. In comparison, the probability of an easy-to diagnose injury, $p^E$, is given by:

$$p^E = (1 - \hat{p}^f(a,r,w))\ \hat{p}^e(a,r,w), \quad (12)$$

$$\text{with } \hat{p}_i^E \;=\; \hat{p}_i^e \;-\; \hat{p}_i^e \, p^f - \; \hat{p}_i^f \; \hat{p}^e, \;\text{ for } i = a, r. \tag{13}$$

Now, let us make the two following plausible assumptions. First, the effects of WC (respectively, UI) benefits on the probability of true easy- and difficult-to-diagnose accidents are not much different, *i.e.*, $\hat{p}_i^d \approx \hat{p}_i^e$ for $i = a, r$. Second, the two last expressions in (11) and in (13) are small (since they involve the probability of each type of accident). Under these assumptions, one obtains, from (11) and (13): $\hat{p}_i^D = \hat{p}_i^E + \hat{p}_i^f$. Therefore the effect of WC (respectively, UI) benefits on the probability of injuries is positive (respectively, negative) and larger (in absolute value) for a difficult-to-diagnose than for an easy-to-diagnose injury. The reason is that, while the probabilities of true easy- and difficult-to diagnose accidents are equally affected by a change in benefits, there is an additionnal source of variation in the case of difficult-to-diagnose accidents: the change in the incentives to report a false accident. In the next section, we will attempt to test empirically these theoretical results.

# 3 Empirical methods and data

This section develops a stochastic multinomial discrete choice model to estimate the parameters of the probability for each worker of the sample considered to experience each of the three following alternatives per month: a difficult-to-diagnose accident, an easy-to-diagnose accident and no workplace accident. It also discusses the data and the variables used in estimations.

## 3.1 Econometric framework

Since we have no information allowing to distinguish between true and false accidents, we cannot directly estimate the first-step random utility model discussed in the preceding section, in which the individual chooses to report or not a false accident. In our model, the realisation of any-one of the three above alternatives partly depends on the choice of the worker, through his decision to report or not a false accident and his choice of the level of accident-preventing efforts. But it also depends on stochastic events that are not under the worker's control and that may influence the state of the nature. Therefore, the random utility model, according to which the realisation of a particular alternative stems entirely from an individual's utility-maximizing decision, but which allows for unobservable preferences heterogeneity, does not directly apply here. However, we will adopt a similar approach by interpreting the latent variable associated with each alternative not as an utility indicator, like in the random utility model, but as a "propensity index" of the alternative. Accordingly, the random term associated with each alternative will take into account not only the presence of heterogeneity in preferences but also stochastic shocks that affect the probability of realisation of the alternative. The model assumes that the realisation of an alternative corresponds to the one with the highest propensity index.

Our econometric framework is an extension to panel data of the approach developed in Bolduc et al. (1996) and Bolduc and Ben-Akiva (1991). For simplicity, it is assumed that the propensity index functions are linear in parameters. For a given worker, $n = 1, ..., N$, the model is

$$y_{int} = \begin{cases} 1 & \text{if } u_{int} \geq u_{knt} \quad \text{for } k = 1,2,3 \\ 0 & \text{otherwise, and} \end{cases} \tag{14}$$

$$u_{int} = x_{int}\beta + \epsilon_{int},$$

where

$$\begin{aligned} i &= 1,2,3 \\ t &= 1, ..., T_n \\ n &= 1, ..., N \end{aligned}$$

In (14), $y_{int}$ denotes the observed realisation associated with alternative i for individual n at time t; $u_{int}$ denotes the corresponding propensity index; $x_{int}$ is the $(1 \times K)$ vector of independent variables; $\beta$ is a $(K \times 1)$ vector of coefficients to be estimated, while $\epsilon_{int}$ is the random disturbance the properties of which are to be described in details below. The main purpose of our econometric analysis is to estimate the parameters $\beta$, given information on the observed accidents, on the vector $x_{int}$ of attributes and given the assumptions pertaining to the distribution of the random disturbance. Note that for certain crucial variables, we will allow the estimated parameter reflecting their impact on the probability of experimenting an accident with easy diagnosis to differ from the parameter reflecting their impact on the probability of experimenting a difficult-to-diagnose injury.

More specifically, our distributional assumptions imply that we write the model as follows:

$$\begin{array}{rcllll} u_{1nt} & = & x_{1nt}\beta + p_{11}w_{1n} & +\sigma_1\xi_{1nt} & +\nu_{1nt} \\ u_{2nt} & = & x_{2nt}\beta + p_{21}w_{1n} + p_{22}w_{2n} & +\sigma_2\xi_{2nt} & +\nu_{2nt} \\ u_{3nt} & = & x_{3nt}\beta & & +\nu_{3nt}, \end{array} \tag{15}$$

where $w_{in}$ and $w_{2n}$ are independent standard normal distributed terms. To get an uniform notation, we pose that: $p_{12} = p_{31} = p_{32} = \sigma_3 = 0$, which makes it possible to write

$$u_{int} = x_{int}\beta + p_i w_n + \sigma_i \xi_{int} + \nu_{int}, \tag{16}$$

where, by definition, $p_i$ denotes row i of matrix $P$ of dimension $(3 \times 2)$ and where $w_n$ is a $(2 \times 1)$ vector with components $w_{1n}$ and $w_{2n}$.

In (16), $p_i w_n$ can be interpreted as a Cholesky representation of bivariate normal terms with zero means. Since $p_i w_n$ is invariant through time, it permits to capture individual specific effects. The term $\sigma_i$ denotes a standard deviation specific to the $i^{th}$ alternative. The $\xi_{int}$ can potentially capture the correlation between the three propensity indexes at a given time period and for a given individual. We tested the presence of such a correlation effect based on a first-order spatial autoregressive (SAR(1)) process (see Bolduc et al. 1996) and we rejected it in all specifications. Therefore, we assume that the $\xi_{int}$'s are i.i.d. standard normal variates.[9] Finally, the $\nu_{int}$ terms, as already indicated, are i.i.d. Gumbell distributed. Given our assumptions, we therefore capture heteroskedastic effects through the $\sigma_i$'s, and time invariant interdependencies between the first two propensity indexes with the help of the $p_{ij}$ Cholesky terms. Note that the restrictions made on the parameters associated with the third index are made for identification purpose. Also this permits to include the standard MNL formulation as a nested sub-model, that is obtained when $\sigma_1 = \sigma_2 = p_{11} = p_{21} = p_{22} = 0$, and a panel MNL, when $\sigma_1 = \sigma_2 = 0$ but with random effects (the $p_i$'s different from zero). Moreover, it nests a hybrid Independent Multinomial Probit (IMNP) specification when the $\sigma_i' s \neq 0$ and $p_{11} = p_{21} = p_{22} = 0$.

[9]With a SAR(1) process, one has: $\xi_{int} = \rho \sum_{k \neq i}^{3} m_{ik}\xi_{knt} + \zeta_{int}$, where $\rho$ is the correlation coefficient $(-1 < \rho < 1)$, where the $m_{ik}$'s are boolean contiguity parameters that are set to one for $i = 1, 2$ and $k = 1, 2$, $i \neq k$, and set to zero otherwise, and where the $\zeta_{int}$ are i.i.d. standard normal variates. The correlation coefficient was not significant in any specification.

In principle, the model could be estimated using the maximum likelihood approach. However, the dimensionality of the response probabilities would require the calculation of multifold integrals of large dimension. Current practice now consists in using either a method of simulated moments (MSM) or a method of maximum simulated likelihood MSL to estimate the unknown parameters of the model. The MSM, suggested in McFadden (1989) and Pakes and Pollard (1989), replaces the multifold normal integrals in a conventional generalized method of moments methodology with smooth (asymptotically) unbiased efficient simulators calculated from an underlying latent variable model[10]. The MSL corresponds to a standard maximum likelihood approach where choice probabilities are replaced with smooth probability simulators[11]. Lee (1992) has derived the asymptotic distribution of both the MSM and the MSL estimators based on smooth probability simulators calculated from a number of draws assumed to increase with the sample size. One of his results indicates that when a smooth probability simulator satisfies the adding-up property, the MSL estimator is asymptotically equivalent to an MSM estimator with known instruments. As he also noted, the simulated likelihood approach may have computational advantages over the MSM method. Therefore, the MSL method is the one that has been used in this paper.

Our assumptions also entail computational simplifications as a natural smooth simulator for the choice probabilities arises. It is expressed as an empirical mean of conditional MNL choice probabilities. It also automatically satisfies the adding-up property. A similar approach was also exploited in Berkovec and Stern (1991).[12]

Given the assumptions made, conditional on $w_n$ and on draws $\xi_{1nt}$, $\xi_{2nt}$, $\xi_{3nt}$ of $\xi_{nt}$ made at a given time period $t$, a probability of realisation for alternative $i$ can be computed as:

$$P_n(i \mid x_{int}, w_n, \xi_{nt}) = \frac{e^{x_{int}\beta + p_i w_n + \sigma_i \xi_{int}}}{\sum_{j=1}^{3} e^{x_{jnt}\beta + p_j w_n + \sigma_j \xi_{jnt}}} \tag{17}$$

[10]For a recent study which used the MSM approach, see Hajivassiliou and McFadden (1990).

[11]See Borsh-Supan and Hajivassiliou (1990), Bolduc and Ben-Akiva (1991) and Bolduc et al. (1996) for empirical studies using this approach.

[12]We also attempted to estimate a panel multinomial probit model (with no logit kernel) using the so-called Geweke-Hajivassiliou-Keane (*e.g.*, see Geweke et al. 1992) choice probability simulator. However, it proved very difficult to estimate in practice and provided estimates very similar to those obtained with our approach. Therefore, in the sequel, the empirical discussion will focus on our hybrid multinomial probit framework.

We denote it as:

$$P_n(i \mid x_{int}, w_n, \xi_{nt}) \equiv \Lambda_n(i \mid w_n, \xi_{nt}).$$

Moreover, the conditional probability of realisation describing the joint observed situations faced by an individual $n$, $\forall t = 1, ..., T_n$, that are incorporated in a $y_n$ vector, is given by:

$$P_n(y_n \mid w_n, \xi_n) = \prod_{t=1}^{T_n} \Lambda_n(i_{nt} \mid w, \xi_t)$$

The unconditional probability of realisation can thus be written as:

$$P_n(y_n) = \int\limits_{\xi} \int\limits_{w} \prod_{t=1}^{T_n} \Lambda_n(i_{nt} \mid w, \xi)\, N(\xi, I_3)\, N(w, I_2) d\xi\, dw, \qquad (18)$$

where $N(z, I_j)$ is the multivariate standard normal density function of a vector $z$ with a covariance matrix given by $I_j$.

Equation(18) is naturally approximated by:

$$f_n(y_n) = \frac{1}{R} \sum_{r=1}^{R} \prod_{t=1}^{T_n} \Lambda_n(i_{nt} \mid w_{nr}, \xi_{ntr}). \qquad (19)$$

where $R$ is the number of draws on $(w_n, \xi_{nt})$ from standard normal density distributions. The log-likelihood is therefore:

$$L^* = \sum_{n=1}^{N} \ln(P_n(y_n))$$

and the simulated log-likehood to be maximized is denoted as

$$L = \sum_{n=1}^{N} \ln(f_n(y_n)), \qquad (20)$$

where $f_n(y_n)$ is calculated using (19).

## 3.2 Data and variables

The original data source for this study follows the evolution of 30,341 workers in the construction industry who worked at least one hour at the James Bay hydro-electric project (a major dam construction plan in northern Quebec) during the period 1976-86. We are able to track the work pattern each month (number of hours worked, occurrence of an accident, etc.) of the workers throughout this period as long as they were working in the construction industry. For tractability, we selected a sample of 9800 of these workers for our estimations.

This sample contained 1269 monthly observations involving a difficult-to-diagnose injury with time lost[13], and 1626 observations involving an easy-to-diagnose injury. Our initial estimations did not converge presumably because of the very low proportion of monthly observations with occurrence of either a difficult-to-diagnose or an easy-to-diagnose injury (less than one percent). Such a problem is frequent with this kind of data, and often leads the researcher to oversample the rare alternative so as to increase the accuracy of his analysis. This was done here up to the point where the proportion of observations with no accident represented 87 %. As shown by Imbens (1992), this choice-based sampling method is not likely to create severe biases in the estimated coefficients except for the intercepts. The latter were corrected using the standard method adopted in the case of MNL estimators (see Imbens 1992). Descriptive statistics for the sample are given in Table 1 at the end of the text.

We distinguish between difficult-to-diagnose injuries and accidents with an easy diagnosis, based on a classification initially used by Dionne and St-Michel (1991). As discussed in Dionne and St-Michel, this categorization was established in consultation with a physician specialized in work-related health problems. The main types of occupational injuries that belong to each group are the following: (1) Easy-to-diagnose injuries: contusion, poisoning, fracture, amputation without permanent partial disability and friction burn; (2) Difficult-to-diagnose injuries: back-related injuries, bursitis and spinal disorders.

Because of important policy changes occurring in 1979, we thought it was reasonable to make our estimations for two different subsamples: 1) a sample covering the years 1977-1978 inclusively, and a sample for the remaining observations. These important policy changes are: 1) the introduction of experience rating on a firm-by-firm basis (CSST, 1982)[14],

[13] An accident with time lost is an accident involving more than one day off work. The permanent disability cases are excluded from the sample.

[14] In Quebec, as in the rest of North America, firms are considered liable for workplace accidents and pay WC insurance premia. Experience rating refers to the adjustment of WC insurance premia to reflect past claim experience.

and 2) the passage from a wage replacement indemnity equal to 75% of gross income (non-taxable) to an indemnity of 90% of the net income (again non-taxable). In particular, the introduction of experience rating may have induced firms, following an increase in WC replacement ratio, to devote more resources to workplace safety because they have to bear more fully the cost of greater incidences of injuries.

We now turn to the explanatory variables (the vector $x$) used in the estimations. Our theoretical model suggests the use of the three following variables: the WC and the UI wage replacement ratios and the wage rate. The WC replacement ratio is defined as the level of benefits divided by the net marginal wage. It has been calculated individually using information on the WC parameters and on the provincial and federal income tax systems in place in each year (see the details in Fortin et al., 1994). In the literature, only Moore and Viscusi (1990) have a replacement ratio calculated individually, using cross-section data. The mean WC replacement ratio in our sample (see Table 1) is 113 percent. One reason why it is greater than 100 percent is that, under the Quebec WC regulations, benefits calculation is based on the earnings of the twelve months preceding the accident. In this calculation, the worker is imputed the same average weekly income for his period off construction as the one he earns during the construction season, which tends to increase the numerator of the ratio. Second, since WC benefits are not taxable and are based either on gross wages (before 1979) or on net *average* wages (after 1979), the (marginal) replacement ratio may be higher than 100 percent for workers with a marginal tax rate higher than a critical level. The UI replacement ratio is also calculated individually and is 0.55, at the mean of our sample.

The WAGE is measured by the worker's net marginal wage rate (in 1981 dollars). There is an important literature showing that the wage and the occupational safety level are the result of a simultaneous decision process (e.g., Garen, 1988), making the wage rate (and the replacement ratios) an endogenous variable[15]. Moreover, individual unobservable characteristics that affect the wage rate (*e.g.*, motivation to work) may also influence the probability of an accident. For these reasons, the wage variable and the two replacement ratios (all in log) have been replaced by generated regressors in the likelihood function, following a two-step approach suggested by Durbin (1970) and Pagan (1984)[16].

[15]For instance, according to the theory of compensating wage differentials, more dangerous jobs lead to a higher wage rate, see Thaler and Rosen (1976).

[16]The variables used in the first-step regression to generate predicted wage rates and the replacement ratios are all the exogenous covariates used in the second step

In keeping with our theoretical discussion, we also consider seasonal dummy variables to capture the fact that workers may have more incentive to report a difficult-to-diagnose injury just before the usual lay-off season in the construction industry. Therefore, we expect the coefficient of the dummy variable for QUARTER 1 (November, December and January) to be a positive and significant determinant of difficult-to-diagnose injuries. We also introduced a variable of unemployment in order to take into account the effect of labour market rationing on the incidence of workplace accidents. The variable UNEMP is defined as the regional unemployment rate as determined by Statistics Canada.

Furthermore, two personal characteristics are taken into account. First, the AGE of the worker is introduced, since it is generally accepted (*e.g.*, see Krueger, 1990) that, *ceteris paribus*, older workers are more risk averse, which may reduce their probability of experiencing an accident. Second, a variable capturing the level of qualification (QUALI) of the worker is included. It is defined as the number of working years required to qualify as a registered member of a given occupation within the construction industry (*e.g.*, carpenter). This variable is intended to capture the worker's skill level. As in Moore and Viscusi (1990), it is expected that more skilled workers are better able to avoid accidents.[17]

In addition, we consider REGIONAL dummies to capture the fact that the nature of the construction projects may vary from one region to another (especially at James Bay), leading to different likelihood of experiencing an accident. After some experimentation, dummies for the regions of Montreal, Quebec, North Shore, James Bay and Abitibi have been used in estimations (other regions are default). Finally, we introduce year dummies to capture omitted fixed effects that vary across time, but not across individuals. These dummies may be useful to account for institutional changes in unemployment insurance and occupational safety policies (like changes in safety-enhancing measures) during the period that may not be captured with our WC and UI variables.

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and $\text{age}^2$, $\text{age}^3$, $\text{qualification}^2$, $\text{qualification}^3$, plus interaction terms between age and qualification (up to the second degree). These additional variables (which are all statistically significant) introduce over-identifying restrictions to the model. Note however that the standard errors of the corresponding estimated coefficients are generally inconsistent. While bootstrapping methods could theoretically be used to generate consistent standard errors estimates, such an approach would be highly time-consuming. One way to circumvent this problem is to interpret our analysis as conditional upon the value of the generated regressors.

[17]In some specifications, we also introduced the variables $\text{age}^2$ and $\text{qualification}^2$ in order to test some over-identifying restrictions of the model. These restrictions were not rejected for any specification at the 5% level.

# 4 Empirical results

Our estimation results are presented in Table 2 (for 1977-1978) and Table 3 (for 1979-1986). Each Table includes four columns. The last column is the panel hybrid IMNP specification, while the three preceding columns are special cases of this general formulation. In column (3), we present a panel MNL specification by setting the $\sigma_i$'s equal to zero; column (2) displays the standard MNL results (by setting both the $\sigma_i$'s and the $p_i$'s equal to zero), and column (1) presents a standard logit model where the two categories of injuries are added together.

First, we performed likelihood ratio tests showing that it was relevant to divide our sample into two sub-periods. Thus the $\chi^2$ statistic corresponding to the panel IMNP specification (column (4)) is 105.23. Further, in both tables, we reject the joint hypothesis that the $\sigma_i$'s and the $p_i$'s are equal to zero. The $\chi^2$ statistics are 22.96 for the period 77-78 and 80.18 for the remaining years. The standard MNL specification (column (2)) is thus rejected by our data. However, we could not reject that the $\sigma_i$'s are jointly equal to zero in both tables, with a $\chi^2$ statistic of 0.04 for the period 77-78 and of 2.98 for the remaining years. Therefore we reject the panel hybrid IMNP specification (column (4)). As a consequence of these various tests, one is led to conclude that the panel MNL model (column (3) of each Table) is not rejected by the data.

In general, the sign, the magnitude and the precision of the estimated coefficients are robust across models. Concerning our main variables of interest, the WC replacement ratio (in log) has everywhere a positive and significant impact on the probability of reporting a difficult-to-diagnose injury, while the impact on the probability of reporting an easy-to-diagnose injury is positive and not significant before 1979, but significant for the period 79-86 (in the simple logit (column (1)), the impact on all types of injuries is positive and significant in each period). In addition, as expected, the impact is always stronger on the probability of reporting a difficult-to-diagnose injury than one with easy diagnosis. The elasticities related to the difficult-to-diagnose injuries range (see Table 4), across the three last columns, from 2.41 to 3.12 before 1979 (0.84 to 1.45 for the period 79-86), while they range from 1.02 to 1.65 before 1979 (0.72 to 1.01 for the period 79-86) for the easy-to-diagnose injuries. Furthermore, the larger elasticities before 1979 are compatible with the introduction of experience rating in 1979, which induces firms to devote more resources to workplace safety, or the monitoring of injuries.

As expected, the UI replacement ratio (in log) has everywhere (including the simple logit) a negative and significant impact on the probability of reporting an injury (expect for the period 79-86 where its impact on easy- to-diagnose injuries is unexpectedly positive but not significant). Interestingly, this is the first result showing that the generosity of UI has an effect on the probability of a workplace accident. The only other paper that has examined this relation is Fortin and Lanoie (1992), who found no such impact presumably because they were using data at the industry level, while we are using data from the construction industry, a sector in which substitution between UI and WC is more likely[18]. Furthermore, the impact is always stronger (in absolute value) on the probability of reporting a difficult-to-diagnose injury than one with easy diagnosis. The elasticities related to the difficult-to-diagnose injuries range across the three last columns from -1.93 to -2.32 before 1979 (-1.24 to -1.81 for the period 79-86), while they range from -1.20 to -1.47 before 1979 (0.22 to 0.55 for the period 79-86) for the easy-to-diagnose injuries. These results confirm that decreases in the generosity of the UI regime lead to higher injury rates reflecting mainly increases in the reporting of difficult-to-diagnose injuries. In fact, when we test jointly whether the impact of the replacement ratios (WC and UI) on each type of injury is the same, we strongly reject the null hypothesis for the period 79-86 (with a $\chi^2$ statistic of 19.72). The fact that the elasticities are smaller for the period 79-86 is again compatible with the introduction of experience rating.

It is also noteworthy that, in general, the impact of WC on the probability of reporting an injury is larger than the absolute value of the UI impact (except for difficult-to-diagnose injuries for the period 79-86). This seems reasonable given that the effect of an insurance regime on the phenomenon it insures is likely to be stronger than the indirect impact of another insurance regime.

The impact of the WC ratio on the probability of reporting an injury for each sub-period is relatively strong compared to the rest of the literature. Typical WC frequency elasticities vary between 0.2 and 0.8 (*e.g.*, Krueger, 1990). Three reasons could be advanced to explain such a result. First, the construction industry presents certain characteristics (regular lay-offs) that make substitution between the two insurance regimes much more likely than in other sectors of economic activity. Moreover, it is likely that the intertemporal labor supply elasticity is

[18] Although they found that increases in the generosity of UI has a negative impact on the duration of WC claims.

higher in the case of individuals who choose to work in a seasonal industry. Second, as mentioned earlier, in Quebec, in contrast with other jurisdictions, the role of the worker's doctor is crucial in determining the duration on WC. Therefore, moral hazard is likely to be more important than elsewhere. Third, the American studies do not account for the possible interaction between the two insurance regimes, which may bias their results[19].

In addition, in line with the preceding results, the probability of reporting a difficult-to-diagnose injury is greater in Quarter 1 (November, December, January) than in the default quarter (Quarter 3: May, June and July - the peak of the year in terms of activity) and this result is significant for the period 77-78. As mentioned earlier, Quarter 1 is typically a "dead season" in the construction industry, and workers may thus be tempted to report a difficult-to-diagnose injury to benefit from WC instead of UI.[20]In Quarter 4 (the end of the high season: August, September, October), the probability of reporting an injury with an easy diagnosis is significantly greater than in Quarter 3, perhaps reflecting the impact of the fatigue following the peak of the season (before 1979, the probability of reporting a difficult-to-diagnose injury is also significantly higher in Quarter 4). Finally, before 1979, the probability of reporting an injury with an easy diagnosis is significantly lower in Quarter 2 (the beginning of the high season) than in Quarter 3.

Concerning the other variables, the impact of the WAGE (in log) on both types of injuries is always positive and significant. Furthermore, this impact is always stronger on the probability of having a difficult-to-diagnose injury than on the probability of having an injury with an easy diagnosis. While a positive sign may partly be explained by the implied increase in the level of WC benefits (since the WC ratio is assumed constant), this may also suggest the existence of an income effect such that high-income individuals can afford to "buy more leisure" and be more often on WC. This argument may be particularly appealing given that our analysis focuses on an industry where the average wage is relatively high[21], while other studies with converse results (negative

[19]Fortin and Lanoie (1992) actually show that the magnitude of the WC impact is reduced when one does not account for the UI variables. This result is not surprising since, given that the UI and WC replacement ratios are positively correlated, omitting the UI ratio will produce a downward bias in the estimates of the effect of the WC ratio.

[20]Another explanation for this result is that the cold winter climate observed in Quebec is likely to lead to more accidents. However, this leaves unexplained the fact that the effect of the cold season is significant only for difficult-to-diagnose injuries.

[21]For instance, during the period 1977-1986, the average weekly wage in the Cana-

sign) are based on more heterogeneous samples (e.g., Butler and Worrall, 1983).

Moreover, the impact of the AGE on the probability of both types of injuries is negative and significant[22], confirming that older workers may be more experienced or more risk averse leading to less accidents. In the same line, the impact of the QUALIFICATION on both types of injuries is always negative and significant, reflecting that better able workers have less accidents. The impact of UNEMP is never significant presumably because the cyclical variations in economic activity are mainly captured by the yearly dummies.

Finally, as regards REGIONAL dummies, a number of remarks are in order. First, before 1979, the probability of experiencing an injury of either type is significantly higher at James Bay than in other regions; this is the only significant effect observed for this period. For the period 79-86 however, the probability of a difficult-to-diagnose injury is significantly lower at James Bay than in the default region (rest of Quebec), while the impact on the probability of reporting an injury with easy diagnosis is not affected. Conversations with officials of the AECQ (Association des entrepreneurs en construction du Québec) provided us with plausible reasons for the preceding results: 1) the authorities responsible for occupational safety and health (OSH) at James Bay increased their monitoring activities after 1980; 2) the Quebec board responsible for OSH also increased its inspections after 1980 with a noticeable effect (a result partly confirmed in Lanoie and Streliski, 1996) and 3) the peak of the construction activities at James Bay was in the period 1977-1978. Furthermore, after 1978, the probability of an injury of either type is significantly larger in the Montreal and Quebec areas than in the default region (although the evidence is not conclusive for difficult-to-diagnose injuries in the Quebec area). Potential explanations are (again from officials of the AECQ): Life is more anonymous in urban centers, while construction projects are smaller (more residential and commercial as opposed to more industrial in the regions) leading to more frequent work interruptions than in the regions, both phenomena may induce workers to more substitution between WC and UI. Finally, the probability of experiencing a difficult-to-diagnose injury is significantly higher in Abitibi than in the default region, while the probability of experiencing an easy-

dian construction industry was \$ 632.61 (Cdn \$ 1986) versus \$ 458.43 in the rest of the economy.

[22] Statistical tests showed that the impact of AGE, QUALI and UNEMP on the probability of one type of injury was not significantly different from their impact on the other type.

to-diagnose injury is significantly higher in the North Shore area than in the default region, both phenomena could be related to the nature of the construction projects or the level of economic activity across regions.

## 5 Conclusion

This paper has provided the first empirical results indicating that WC insurance could affect not only the frequency or the duration of workplace accident claims, but also the composition of these reported accidents. Our theoretical framework extended the present literature, which simply considers that a worker can either have an accident or not, to the case where he can also report a false difficult-to-diagnose injury. Our model predicts that, under reasonable assumptions, an increase in the wage replacement ratio under WC (or a decrease in the UI wage replacement ratio) leads to a larger increase in the probability of reporting a difficult-to-diagnose injury than in the probability of reporting an easy-to-diagnose injury.

Panel data on 9800 workers in the Quebec construction industry over each month of the period 1977-1986 were used for the estimations. Our empirical approach is an extension to panel data of the method developed in Bolduc et al. (1996) and Bolduc and Ben-Akiva (1991). The parameters of the model were estimated using a three alternative panel hybrid MultiNomial Probit (MNP) framework. Our results confirmed our theoretical prediction that an increase in the generosity of WC (and a decrease in the generosity of UI) leads to a larger increase in the probability of reporting a difficult-to-diagnose injury than in the probability of reporting an easy-to-diagnose injury. In line with this result, we also showed that the probability to report a difficult-to-diagnose injury is significantly greater in winter (the dead season in the construction industry) than in other seasons. These empirical evidence are consistent with the presence of moral hazard and of a substitution between WC and UI in the construction industry.

## References


[1] Baltagi, B.H. (1995) *Econometric Analysis of Panel Data*, Chichester: John Wiley & Sons.

[2] Berkovec, J and S. Stern (1991), "Job Exit Behavior of Older Men" *Econometrica*, 59, 189-210.

[3] Bolduc, D., B. Fortin and M.-A. Fournier (1996), "The Impact of Incentive Policies on the Practice Location of Doctors: A Multinomial Probit Analysis", *Journal of Labor Economics*, 14, 703-732.

[4] Bolduc, D. and M. Ben-Akiva (1991), "A Multinomial Probit Formulation for Large Choice Sets", *Proceedings of the 6th International Conference on Travel Behavior*, Quebec.

[5] Borsch-Supan, A. and V. Hajivassiliou (1990), " Smooth Unbiased Multivariate Probability Simulators for Maximum Likelihood Estimation of Limited Dependent Variable Models", *Journal of Econometrics*, 58, 347-68.

[6] Butler, R.J. and J.D. Worrall (1983), "Workers'Compensation: Benefit and Injury Claim Rates in the Seventies", *Review of Economics and Statistics*, 60, 580-589.

[7] Card, D. and B.P. McCall (1994), "Is Workers'Compensation Covering Uninsured Medical Costs? Evidence from the 'Monday Effect", Working Paper no. 327, Princeton: Princeton University, Industrial Relations Section.

[8] CSST (1982), *Annual Report 1982*, Montreal: Quebec government.

[9] CSST (1984), *Statistiques sur les lésions professionnelles 1980-84*, Montreal: Quebec government.

[10] Dionne, G. and P. St-Michel (1991), "Workers' Compensation and Moral Hazard", *Review of Economics and Statistics*, 73, 236-244.

[11] Durbin, J. (1970), "Testing for Serial Correlation in Least-Squares Regression When Some of the Regressors are Lagged Dependent Variables", *Econometrica*, 38, 410-421.

[12] Elrod T. and M. Keane (1995), "A Factor-analytic Probit Model for Representing the Market Structure with Panel Data", *Journal of Marketing Research*, 32, 1-16.

[13] Fortin, B. and P. Lanoie (1992), "Substitution between Unemployment Insurance and Workers' Compensation: An Analysis Applied to the Risk of Workplace Accidents", *Journal of Public Economics*, 49, 287-312.

[14] Fortin, B., P. Lanoie and Christine Laporte (1994), "The Effect of Unemployment Insurance on the Duration of Workplace Accidents", Discussion Paper no IEA, 94-05, Montreal: Ecole des Hautes Etudes Commerciales.

[15] Garen, J. (1988), "Compensating Wage Differentials and the Endogeneity of Job Riskiness", *Review of Economics and Statistics*, 9-16.

[16] Geweke, J., M. Keane and D. Runkle (1992), Alternative Computational Approaches to Inference in the Multinomial Probit Model, Research Department, Federal Reserve Bank of Minneapolis.

[17] Guilkey, D.K. and J.L. Murphy (1993), "Estimating and Testing in the Random Effects Probit Model", *Journal of Econometrics*, 59, 301-317.

[18] Hajivassiliou, V. and D. McFadden (1990), "The Method of Simulated Scores for the Estimation of LDV Models with an Application to External Debt Crises", Cowles Foundation Discussion Paper no. 967, Yale University.

[19] Imbens, G.W. (1992) "An Efficient Method of Moment Estimator for Discrete Choice Models With Choice Based Sampling", *Econometrica*, 60, 1187-1214.

[20] Kesselman, J. (1989), "Income Tax Evasion: An Intersectoral Analysis", *Journal of Public Economics*, 38, 137-182.

[21] Kniesner, T.J. and J.D. Leeth (1988), "Simulating Hedonic Labor Market Models: Computational Issues and Policy Applications", *International Economic Review*, 29, 755-790.

[22] Krueger, A.B. (1988), "Moral Hazard in Workers' Compensation Insurance, Mimeo, Princeton University.

[23] Krueger, A.B. (1990), "Incentive Effects of Workers' Compensation Insurance", *Journal of Public Economics* 41, 73-99.

[24] Lanoie, P. (1991), "Occupational Safety and Health: A Problem of Double or Single Moral Hazard", *Journal of Risk and Insurance*, 58, 80-100.

[25] Lanoie, P. and D.Streliski (1996), "L'impact de la réglementation en matière de santé et sécurité du travail sur le risque d'accident au Québec: de nouveaux résultats", *Relations Industrielles\Industrial Relations*, 51, 778-801.

[26] Lee, L.F. (1992), "On Efficiency of Methods of Simulated Moments and Maximum Likelihood Estimation of Discrete Response Models", *Econometric Theory*, 8, 518-52.

[27] McFadden, D. (1989), "A Method of Simulated Moments for Estimation of the Multinomial Probit Without Numerical Integration" *Econometrica*, 57, 995-1026.

[28] Meyer, B.D., W.K. Viscusi and D.L. Durbin (1995), "Workers' Compensation and Injury Duration: Evidence from a Natural Experiment", *American Economic Review*, 85, 322-40.

[29] Moore, M.J. and K.W. Viscusi (1990), *Compensation Mechanisms for Job Risks, Wages, Workers' Compensation and Product Liability*, Princeton: Princeton University Press.

[30] Pagan, A. (1984), "Econometric Issues in the Analysis of Regressions with Generated Regressors", *International Economic Review*, 25, 221-247.

[31] Pakes A. and D. Pollard (1989), " Simulation and the Asymptotics of Optimization Estimators", *Econometrica*, 57, 1989, 1027-1057.

[32] Ruser, J.W. (1985), "Workers'Compensation Insurance, Experience-Rating and Occupational Injuries", *Rand Journal of Economics*, 16, 487-503.

[33] Staten, M.E. and J. Umbeck (1982), "Information Costs and Incentives to Shirk: Disability Compensation of Air Traffic Controllers", *American Economic Review*, 73, 1023-37.

[34] Smith, R.S. (1989) "Mostly on Monday: Is Workers' Compensation Covering Off-The-Job Injuries", in Appel, D. *Benefits, Costs and Cycles in Workers'Compensation Insurance*, Norwood, Kluwer Academic Press, 1989.

[35] Thaler, R. and S. Rosen (1976), "The Value of Life Saving", in *Household production and Consumption*, ed. by N.E. Terleckyj. New York: NBER Press, Columbia University.

**TABLE 1**

**DESCRIPTIVE STATISTICS**[a]

| **Variable** | **Means** | **Stand. Dev.** | **Min** | **Max** |
|---|---|---|---|---|
| **Difficult-to-diagnose** | 0.44 | 0.50 | 0 | 1 |
| **Easy-to-diagnose** | 0.56 | 0.50 | 0 | 1 |
| **WC replacement ratio** | 1.13 | 0.11 | 0.28 | 1.51 |
| **UI replacement ratio** | 0.55 | 0.09 | 0.10 | 0.67 |
| **Regional unemployment rate** | 12.63 | 2.86 | 6.60 | 21.60 |
| **Age** | 37.38 | 10.24 | 17 | 70 |
| **Years of qualification** | 1.52 | 1.48 | 0 | 5 |
| **Region** | | | | |
| James Bay | 0.29 | 0.45 | 0 | 1 |
| Quebec | 0.13 | 0.34 | 0 | 1 |
| Montreal | 0.25 | 0.43 | 0 | 1 |
| North Shore | 0.04 | 0.19 | 0 | 1 |
| Abitibi | 0.06 | 0.24 | 0 | 1 |
| **Quarter** | | | | |
| November, December, January | 0.21 | 0.41 | 0 | 1 |
| February, March, April | 0.19 | 0.39 | 0 | 1 |
| May, June, July | 0.28 | 0.45 | 0 | 1 |
| August, September, October | 0.32 | 0.47 | 0 | 1 |
| **Year** | | | | |
| 1977 | 0.13 | 0.34 | 0 | 1 |
| 1978 | 0.14 | 0.35 | 0 | 1 |
| 1979 | 0.13 | 0.33 | 0 | 1 |
| 1980 | 0.11 | 0.31 | 0 | 1 |
| 1981 | 0.11 | 0.31 | 0 | 1 |
| 1982 | 0.08 | 0.26 | 0 | 1 |
| 1983 | 0.07 | 0.25 | 0 | 1 |
| 1984 | 0.08 | 0.27 | 0 | 1 |
| 1985 | 0.08 | 0.27 | 0 | 1 |
| 1986 | 0.08 | 0.27 | 0 | 1 |

a 391 030 observations, 2895 accidents and 9807 workers

**TABLE 2**

**PROBABILITY OF WORKPLACE ACCIDENTS (1977-1978)**
(Standard errors in parantheses)

| Variable | Logit | | Multi. Logit | | Multi. Logit Panel | | Multi. Probit* Panel | |
|---|---|---|---|---|---|---|---|---|
| **Constant** | -14.362 | (2.125) | | | | | | |
| Difficult diagnosis | | | -14.48 | (2.82 ) | -18.29 | (3.61 ) | -18.39 | (3.66 ) |
| Easy diagnosis | | | -12.27 | (2.58 ) | -15.99 | (3.40 ) | -16.19 | (3.57 ) |
| **ln($REPL_{wc}$)** | 2.157 | (0.648) | | | | | | |
| Difficult diagnosis | | | 2.37 | (0.951) | 3.21 | (1.34 ) | 3.22 | (1.36 ) |
| Easy diagnosis | | | 0.994 | (0.819) | 1.79 | (1.17 ) | 1.78 | (1.19 ) |
| **ln($REPL_{ui}$)** | -1.964 | (0.478) | | | | | | |
| Difficult diagnosis | | | -1.92 | (0.692) | -2.45 | (0.912) | -2.46 | (0.925) |
| Easy diagnosis | | | -1.13 | (0.599) | -1.60 | (0.870) | -1.60 | (0.888) |
| **ln(UNEMP)** | -0.928 | (0.597) | -0.887 | (0.660) | -0.770 | (0.869) | -0.780 | (0.872) |
| **ln(AGE)** | -0.810 | (0.195) | -0.831 | (0.212) | -0.969 | (0.297) | -0.972 | (0.303) |
| **QUALI** | -0.264 | (0.054) | -0.261 | (0.057) | -0.286 | (0.080) | -0.289 | (0.082) |
| **ln(WAGE)** | 5.595 | (0.738) | | | | | | |
| Difficult diagnosis | | | 5.19 | (1.01 ) | 6.38 | (1.37 ) | 6.41 | (1.38 ) |
| Easy diagnosis | | | 4.63 | (0.896) | 5.80 | (1.36 ) | 5.86 | (1.43 ) |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Regions** | | | | | | | | |
| **Montreal** | -0.023 | (0.236) | | | | | | |
| Difficult diagnosis | | | -0.242 | (0.415) | -0.159 | (0.475) | -0.165 | (0.480) |
| Easy diagnosis | | | 0.400 | (0.335) | 0.514 | (0.407) | 0.520 | (0.413) |
| **Quebec** | 0.136 | (0.250) | | | | | | |
| Difficult diagnosis | | | 0.399 | (0.375) | 0.360 | (0.434) | 0.369 | (0.437) |
| Easy diagnosis | | | 0.099 | (0.362) | 0.021 | (0.411) | 0.021 | (0.419) |
| **James Bay** | 0.992 | (0.207) | | | | | | |
| Difficult diagnosis | | | 0.998 | (0.322) | 1.26 | (0.403) | 1.26 | (0.408) |
| Easy diagnosis | | | 1.10 | (0.282) | 1.35 | (0.354) | 1.37 | (0.370) |
| **North Shore** | -0.285 | (0.481) | | | | | | |
| Difficult diagnosis | | | -0.261 | (0.767) | -0.090 | (0.962) | -0.083 | (0.967) |
| Easy diagnosis | | | -0.175 | (0.636) | 0.071 | (0.757) | 0.079 | (0.768) |
| **Abitibi** | 0.260 | (0.329) | | | | | | |
| Difficult diagnosis | | | 0.089 | (0.531) | 0.345 | (0.637) | 0.344 | (0.639) |
| Easy diagnosis | | | 0.317 | (0.435) | 0.530 | (0.529) | 0.535 | (0.540) |
| **Quarters** | | | | | | | | |
| **Quarter 1** | 0.460 | (0.155) | | | | | | |
| Difficult diagnosis | | | 0.554 | (0.249) | 0.771 | (0.310) | 0.777 | (0.312) |
| Easy diagnosis | | | 0.180 | (0.215) | 0.368 | (0.267) | 0.374 | (0.277) |

* This corresponds to an hybrid multinomial probit (that is, with a logit kernel).

**TABLE 2 (cont'd)**

| Variable | Logit | | Multi. Logit | | Multi. Logit Panel | | Multi. Probit* Panel | |
|---|---|---|---|---|---|---|---|---|
| **Quarter 2** | -0.355 | (0.194) | | | | | | |
| Difficult diagnosis | | | -0.353 | (0.311) | -0.406 | (0.371) | -0.399 | (0.373) |
| Easy diagnosis | | | -0.630 | (0.266) | -0.767 | (0.349) | -0.771 | (0.355) |
| **Quarter 4** | 0.378 | (0.138) | | | | | | |
| Difficult diagnosis | | | 0.413 | (0.231) | 0.631 | (0.277) | 0.633 | (0.282) |
| Easy diagnosis | | | 0.276 | (0.187) | 0.468 | (0.235) | 0.471 | (0.246) |
| **Years** | | | | | | | | |
| **1978** | 1.039 | (0.151) | 1.01 | (0.165) | 1.33 | (0.249) | 1.34 | (0.258) |
| $\boldsymbol{\sigma_1}$ | | | | | | | 0.092 | (1.24 ) |
| $\boldsymbol{\sigma_2}$ | | | | | | | 0.419 | (0.977) |
| $\mathbf{p_{11}}$ | | | | | 1.58 | (0.345) | 1.59 | (0.365) |
| $\mathbf{p_{21}}$ | | | | | 0.294 | (0.489) | 0.339 | (0.509) |
| $\mathbf{p_{22}}$ | | | | | -0.818 | (0.558) | -0.867 | (0.540) |
| **Log-likelihood** | -2258.54 | | -1201.38 | | -1189.92 | | -1189.90 | |

* This corresponds to an hybrid multinomial probit (that is, with a logit kernel).

**TABLE 3**

**PROBABILITY OF WORKPLACE ACCIDENTS (1979-1986)**
(Standard errors in parantheses)

| **Variable** | **Logit** | | **Multi. Logit** | | **Multi. Logit Panel** | | **Multi. Probit* Panel** | |
|---|---|---|---|---|---|---|---|---|
| **Constant** | -7.040 | (0.640) | | | | | | |
| Difficult diagnosis | | | -8.88 | (0.900) | -10.08 | (1.00 ) | -10.15 | (1.05 ) |
| Easy diagnosis | | | -6.87 | (0.862) | -7.71 | (0.973) | -8.18 | (1.12 ) |
| **Log($REPL_{wc}$)** | 0.780 | (0.373) | | | | | | |
| Difficult diagnosis | | | 0.847 | (0.544) | 1.31 | (0.590) | 1.44 | (0.605) |
| Easy diagnosis | | | 0.716 | (0.527) | 1.05 | (0.548) | 1.09 | (0.611) |
| **Log($REPL_{ui}$)** | -0.523 | (0.243) | | | | | | |
| Difficult diagnosis | | | -1.25 | (0.347) | -1.70 | (0.391) | -1.81 | (0.405) |
| Easy diagnosis | | | 0.542 | (0.355) | 0.202 | (0.384) | 0.295 | (0.432) |
| **Log(UNEMP)** | -0.153 | (0.153) | -0.117 | (0.185) | -0.061 | (0.212) | -0.080 | (0.225) |
| **Log(AGE)** | -0.725 | (0.083) | -0.735 | (0.101) | -0.938 | (0.123) | -1.01 | (0.140) |
| **QUALI** | -0.144 | (0.017) | -0.142 | (0.021) | -0.172 | (0.025) | -0.185 | (0.028) |
| **Log(WAGE)** | 2.403 | (0.219) | | | | | | |
| Difficult diagnosis | | | 2.76 | (0.326) | 3.38 | (0.363) | 3.52 | (0.388) |
| Easy diagnosis | | | 2.27 | (0.309) | 2.79 | (0.348) | 3.03 | (0.418) |

* This corresponds to an hybrid multinomial probit (that is, with a logit kernel).

**TABLE 3 (cont'd)**

| Variable | Logit | | Multi. Logit | | Multi. Logit Panel | | Multi. Probit* Panel | |
|---|---|---|---|---|---|---|---|---|
| **Regions** | | | | | | | | |
| **Montreal** | 0.471 | (0.063) | | | | | | |
| Difficult diagnosis | | | 0.325 | (0.415) | 0.341 | (0.110) | 0.336 | (0.113) |
| Easy diagnosis | | | 0.635 | (0.091) | 0.640 | (0.102) | 0.716 | (0.130) |
| **Quebec** | 0.226 | (0.078) | | | | | | |
| Difficult diagnosis | | | 0.147 | (0.117) | 0.141 | (0.136) | 0.143 | (0.139) |
| Easy diagnosis | | | 0.226 | (0.113) | 0.207 | (0.124) | 0.225 | (0.139) |
| **James Bay** | -0.043 | (0.084) | | | | | | |
| Difficult diagnosis | | | -0.308 | (0.131) | -0.328 | (0.144) | -0.326 | (0.145) |
| Easy diagnosis | | | 0.181 | (0.120) | 0.172 | (0.129) | 0.190 | (0.145) |
| **North Shore** | 0.305 | (0.110) | | | | | | |
| Difficult diagnosis | | | -0.280 | (0.208) | -0.230 | (0.228) | -0.230 | (0.231) |
| Easy diagnosis | | | 0.574 | (0.153) | 0.635 | (0.169) | 0.746 | (0.212) |
| **Abitibi** | 0.290 | (0.092) | | | | | | |
| Difficult diagnosis | | | 0.340 | (0.139) | 0.390 | (0.163) | 0.392 | (0.165) |
| Easy diagnosis | | | 0.169 | (0.145) | 0.204 | (0.161) | 0.207 | (0.180) |
| **Quarters** | | | | | | | | |
| **Quarter 1** | 0.133 | (0.058) | | | | | | |
| Difficult diagnosis | | | 0.202 | (0.094) | 0.155 | (0.103) | 0.163 | (0.104) |
| Easy diagnosis | | | 0.072 | (0.089) | 0.041 | (0.095) | 0.036 | (0.108) |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Quarter 2** | 0.190 | (0.053) | | | | | | |
| Difficult diagnosis | | | 0.057 | (0.101) | 0.086 | (0.111) | 0.088 | (0.113) |
| Easy diagnosis | | | -0.003 | (0.094) | 0.037 | (0.100) | 0.043 | (0.113) |
| **Quarter 4** | 0.190 | (0.053) | | | | | | |
| Difficult diagnosis | | | 0.052 | (0.087) | 0.033 | (0.096) | 0.032 | (0.097) |
| Easy diagnosis | | | 0.237 | (0.078) | 0.230 | (0.085) | 0.263 | (0.099) |
| **Years** | | | | | | | | |
| **1979** | -0.291 | (0.079) | -0.316 | (0.092) | -0.374 | (0.103) | -0.405 | (0.110) |
| **1980** | -0.192 | (0.079) | -0.289 | (0.093) | -0.124 | (0.109) | -0.137 | (0.115) |
| **1982** | 0.103 | (0.091) | 0.067 | (0.110) | 0.092 | (0.126) | 0.093 | (0.134) |
| **1983** | 0.074 | (0.092) | 0.099 | (0.112) | 0.190 | (0.126) | 0.205 | (0.134) |
| **1984** | 0.127 | (0.086) | 0.139 | (0.105) | 0.151 | (0.118) | 0.174 | (0.125) |
| **1985** | 0.219 | (0.080) | 0.248 | (0.097) | 0.277 | (0.109) | 0.290 | (0.116) |
| **1986** | 0.351 | (0.108) | 0.367 | (0.096) | 0.462 | (0.108) | 0.475 | (0.117) |
| $\boldsymbol{\sigma_1}$ | | | | | | | 0.162 | (0.470) |
| $\boldsymbol{\sigma_2}$ | | | | | | | 0.989 | (0.407) |
| $\mathbf{p_{11}}$ | | | | | 0.808 | (0.077) | 0.921 | (0.118) |
| $\mathbf{p_{21}}$ | | | | | -0.091 | (0.120) | -0.038 | (0.157) |
| $\mathbf{p_{22}}$ | | | | | -0.405 | (0.185) | 0.467 | (0.167) |
| **Log-likelihood** | -14284.69 | | -6818.53 | | -6779.93 | | -6778.44 | |

* This corresponds to an hybrid multinomial probit (that is, with a logit kernel).

**TABLE 4**

**ESTIMATED ELASTICITIES**

| | 1977-1978 | | 1979-1986 | |
|---|---|---|---|---|
| | $REPL_{wc}$ | $REPL_{ui}$ | $REPL_{wc}$ | $REPL_{ui}$ |
| **Logit** | 1.6016 | -1.4016 | 0.7000 | -0.3322 |
| **Multi. Logit** | | | | |
| Difficult diagnosis | 2.4096 | -1.9277 | 0.8374 | -1.2426 |
| Easy diagnosis | 1.0274 | -1.1986 | 0.7194 | 0.5501 |
| **Multi. Logit Panel** | | | | |
| Difficult diagnosis | 3.1108 | -2.3033 | 1.2925 | -1.6693 |
| Easy diagnosis | 1.6539 | -1.4668 | 1.0341 | 0.2229 |
| **Multi. Probit (Kernel) Panel** | | | | |
| Difficult diagnosis | 3.1229 | -2.3164 | 1.4506 | -1.8132 |
| Easy diagnosis | 1.6445 | -1.4620 | 1.0149 | 0.2985 |

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