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Workers' Compensation and Moral Hazard in Tunisia

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Abstract:

Moral hazard is a problem of asymmetric information that plays a central role in numerous contractual relationships and that may lead to a suboptimal resource allocation. Both ex ante and ex post moral hazard problems in workers' compensation have been extensively analyzed in developed countries. To our knowledge, this is the first analysis on this topic in a developing country, Tunisia. It is particularly important to study moral hazard problems in developing countries since the negative impacts of such problems could be exacerbated in the developing world. We apply the methodology of Dionne and St-Michel (1991) to test the presence of ex post moral hazard. We find that an increase in the generosity of workers'compensation leads to longer periods out of work for recovery. This increase is more pronounced in the case of difficult to diagnose injuries. We present evidence that moral hazard problems are relatively more acute in developing countries than in advanced economies.

Résumé:

L'aléa moral est un problème d'asymétrie d'information qui joue un rôle crucial dans de nombreuses relations contractuelles et qui peut mener à une allocation sous-optimale des ressources. Les deux problèmes d'aléa moral, ex ante et ex post, liés à la compensation des victimes des accidents de travail ont été analysés en détails dans les pays développés. À notre connaissance, il s'agit de la première analyse sur ce sujet dans un pays en développement, la Tunisie. Il est particulièrement important d'étudier les problèmes d'aléa moral dans les pays en développement puisque les impacts négatifs de ces problèmes peuvent être exacerbés dans le contexte de ces pays. Nous appliquons la méthodologie de Dionne et St-Michel (1991) pour tester la présence de risque moral ex post. Nous constatons que l'augmentation de la générosité de la compensation conduit à de plus longues périodes de récupération avant la reprise du travail. Cette augmentation est plus prononcée dans le cas de blessures difficiles à diagnostiquer. Nous montrons empiriquement que le problème d'aléa moral est relativement plus sévère dans les pays en développement que dans les économies avancées.

Key words: workers' compensation, workplace accidents severity, moral hazard, hard-to-diagnose injuries.

Mots clés: assurance accident, sévérité des accidents du travail, risque moral, blessures difficiles à diagnostiquer.

Introduction

When an economic agent is not held accountable for the full cost of his or her actions, the situation may create a moral hazard: through doing what is personally optimal, the agent may behave in ways that are socially suboptimal (Holmström, 1979). Moral hazard is a problem of asymmetric information that plays a central role in numerous contractual relationships, and researchers have found evidence of moral hazard in many contexts, particularly in the world of insurance contracts.

In that area, two types of moral hazard have been observed. The first ("ex ante moral hazard") is related to suboptimal self-prevention activities affecting probabilities of accidents. Specific measures must be introduced in insurance contracts to reduce the negative effects of this problem, like partial insurance coverage or premium levels based on past experience. The second type of moral hazard ("ex post") relates to the agent's activities whenever the accident occurs. Since insured are more informed than insurer about the true state of the world, they can influence the distribution of losses in order to obtain higher insurance coverage for an accident. For example, an agent could ask for repairs to his car, or additional medical services, which are unrelated to the accident. Or he could even obtain a period of absence from work longer than that associated with his true state of health. Measures to attenuate these problems include partial insurance or direct control by the insurer by means of auditing (Dionne and St-Michel, 1991, Dionne 2013).

Exogenous changes in an insurance regime can allow researchers to isolate moral hazard. It can be interpreted as a laboratory experiment if certain conditions are met. In particular, it is important to have a control group who goes through the same insurance changes, but who does not have the same information problems as those anticipated. For example, if one expects that some workers with specific medical diagnoses (hard to verify) have greater information asymmetry with the insurer, there must be other workers experiencing the same insurance changes at the same time, but whose information asymmetry is weaker (easy to diagnose and verify).

Dionne and St-Michel (1991) managed to bring these conditions together when studying the impact of an increase in insurance coverage from workers' compensation (WC) for workplace accidents in Quebec occurring in 1979. In particular, they showed that better insurance led to an increase in the duration for absence from work for injured workers with a diagnosis with more information asymmetry (hard-to-diagnose) between the worker and the insurer, as represented by a doctor. The workers of the control group (those with easy-to-diagnose injuries) did not change their behavior. Arguably, they have identified an ex post moral hazard[2].

In this paper, we apply the methodology developed by Dionne and St-Michel (1991) to the situation prevailing in Tunisia. The institutional context is similar; that is, in 1995, there was a significant increase in the generosity of the Tunisian WC regime. There are very few studies on the existence of moral hazard problems in insurance contracts in developing countries and, to our knowledge, none related to workers compensation.[3]

It is important to study moral hazard in developing countries, especially in labor markets, for many reasons: 1) working conditions are more difficult in these countries so that the need for efficient insurance contracts could be more acute than in wealthier countries (e.g., Emmelhainz and Adams, 2006); 2) in spite of this pressing need, providing insurance in developing countries is subject to a large array of problems (correlated risks, transaction costs, lack of reliable data, etc.) that may jeopardize the chances of success of emerging insurance markets (Biener and Eling, 2012); 3) less developed institutions and markets make information asymmetries more likely in developing countries than in developed ones; for instance, quality of diagnoses could be inferior in developing countries, or the strength of the informal networks may make the collusion easier between workers and physicians "against" the insurer; and 4) developing an adequate and efficient social security system is certainly one of the main challenges of Africa in the near future (e.g. see the African Economic Outlook 2014, World Bank (2012), or African Development Bank Group, (2014)), so that more research is needed to improve our understanding of the potential drawbacks of different options. Overall, it is thus useful and relevant to undertake this study and to compare our results with those of Dionne and St-Michel to draw the appropriate conclusions.

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[2] See Fortin and Lanoie (2003) and Butler et al. (2013) for surveys of studies on the presence of moral hazard related to workers' compensation regimes. For papers using the distinction between easy and hard-to-diagnose injuries, see Butler et al. (1996), Ruser (1998), Fortin et al. (1999), Campolieti (2002), Bolduc et al., (2002) and Boden and Ruser, 2003. Workers can also simulate accidents (Staten and Umbeck, 1982 and Butler et al., 1997), or report an accident unrelated to their activities as a workplace accident (Smith, 1989).

[3] Olayiwola and Olaniyan (2014) examine the presence of moral hazard in health insurance in Nigeria, while Biener et al. (2014) investigate, through experimental economics, the existence and the mitigation of ex ante moral hazard in a low-income insurance market in the Philippines. However, moral hazard in developing countries' credit markets seems to have received more attention (e.g. Ebeke, 2012).

In order to do so, we have access to a unique database. We follow more than 300 000 workers in Tunisia between 1993 and 2000; i.e., before and after 1995, when there was a regime change in coverage of health insurance, through the adoption of a compulsory insurance scheme characterized by a more generous public compensation. Our database contains all information related to workplace accidents experienced by these workers, in particular the types of injuries they had and the duration of their recovery periods. Furthermore, we have information on the demographic characteristics of injured workers, and on other control variables related to the administrative region and industry in which the injured employee works.

This kind of data contains censored observations for workers who had not returned to work at the end of their disability period. If one treats these non-completed claims as terminated, this may introduce a bias in the estimations as longer durations are ignored. To account for this situation, we choose a hazard model estimation technique[4]. One of the benefits of the hazard model specification over the least squares used by Dionne and St-Michel (1991) is that it can easily accommodate these censored data. In addition, hazard models with frailty can account for unobserved heterogeneity.

Our results confirm that ex post moral hazard is present in the Tunisian labor market. It follows that increasing the generosity of compensation increases the severity of accidents in Tunisia, and this increase is relatively more pronounced in the case of difficult to diagnose injuries. These results are consistent with those in Dionne and St-Michel (1991), and we even provide evidence that moral hazard problems are relatively more acute in developing countries than in advanced economies.

The rest of the paper is organized as follows. In the first section, we present a brief description of the Tunisian WC system. The theoretical workplace model is detailed in the second section. Section 3 is devoted to the empirical model and the econometric strategy, while section 4 presents and discusses the results. The final section concludes.

[4] For a good discussion on hazard models in labor economics, see Cleves et al. (2010) and Kiefer and Neumann (2006).

1. Description of the Tunisian Workers' Compensation system

At the beginning of the 90's, Tunisia was negotiating a free trade agreement with the European Union. In particular, it was necessary for the country to modernize its social insurance system to ensure that Tunisian workers would not be negatively affected by this change, and to make the agreement more acceptable for European countries. The agreement was actually signed on July 17th 1995.

In this context, the Tunisian government has paid more attention to occupational safety and health. First, an effort was made on improving safety: 1) new safety standards were adopted in 1995 and the frequency of inspections was increased; 2) an experience rating system ("bonus-malus") was introduced so that firms' insurance premia would reflect their past accident experience, providing them with an incentive to improve safety; 3) grants were provided to firms that invested in prevention projects and 4) safety and health committees were created within firms of 40 employees and more.

Second, the government has been active on the insurance front with the following measures, most of them put in place in 1995: 1) WC insurance was provided by the public sector (instead of private), more specifically by the CNSS (Caisse Nationale de la Sécurité Sociale), and coverage was extended to nearly all workers; previously the workers of the agricultural sector were excluded; 2) the insurance premia were lowered; 3) more generous benefits in case of accidents or injuries were introduced; the wage replacement rate for temporary total disabilities[5] went from 50 to 66.67% of net daily wage. For a permanent disability, a victim is entitled to a pension equal to the product of his annual compensation multiplied by the rate of incapacity. This compensation is doubled if the disability rate exceeds 50%.

[5] Benefits have also been improved for accidents resulting in permanent disabilities or deaths.

In the context of our study, it seems fairly evident that the change in the Tunisian workers' compensation regime is exogenous and can thus be interpreted as a laboratory experiment (for further discussion, see Chiappori and Salanié, 2013, or Cummins et al. 2001).

2. Theoretical model[6]

As stated in the introduction, we want to concentrate on "ex post" moral hazard characterizing the insured's behavior under asymmetric information, once the accident has occurred. Let E_i denotes the number of extra days of absence from work over the level of corresponding to full information for a given diagnosis i: $E_i = \left(L_i - \overline{L_i}\right)$ where L_i is the total number of compensation days and $\overline{L_i}$ is the number of compensation days under full information. $c(E_i)$ denotes the cost of finding and convincing a physician to write a medical report permitting such level of compensation, which is an increasing function of E_i. The benefit ($\alpha w E_i$, where α is the insurance coverage ($0 < \alpha < 1$) and w, the wage rate) is random since there is a probability p_i that the worker will not receive any compensation. When the report is rejected, $E_i = 0$. Under full information, $p_i = 1$. Under asymmetric information $p_i < 1$ and is a decreasing function of the degree of asymmetric information.

The worker maximizes over E_i :

$$\left(1-p_i\right)U\left(\gamma_i + \alpha w E_i - c\left(E_i\right)\right) + p_i U\left(\gamma_i - c\left(E_i\right)\right) \tag{1}$$

where γ_i is the wealth corresponding to $\overline{L_i}$ and U is the von Neuman-Morgenstern utility function $\left(U^{'}(.)\rangle 0, U^{''}(.) \leq 0\right)$.

The variation of E_i^* with respect to α :

$$\frac{dE_i^*}{d\alpha} = \frac{-1}{\Delta}\left\{\left(1-p_i\right)U^{'}\left(\gamma_i + \alpha w E_i - c\left(E_i\right)\right) \times w\left[1 - r_i\left(w\alpha - c^{'}\right)E_i\right]\right\} \tag{2}$$

[6] This section is largely inspired by Dionne and St-Michel (1991).

where r_i is the Arrow-Pratt measure of absolute risk aversion evaluated at $\left(\gamma_i + \alpha w E_i - c\left(E_i\right)\right)$ and Δ denotes the second order condition.

When $r_i = 0$ (risk neutrality), (2) is positive for all $p_i < 1$ and null under full information. Furthermore, the variation of E_i^* with respect to an increase in the replacement ratio (α) is larger for illness that are more difficult to diagnose (low p_i). Under risk aversion ($r_i > 0$), $\frac{dE_i}{d\alpha} \rangle 0$ when $r_i\left(w\alpha - c^{'}\right)E_i \langle 1$. Hence, it will remain larger for injuries that are more difficult to diagnose.

Thus, the theoretical model of Dionne and St-Michel (1991) predicts that increasing the generosity of compensation increases the severity of accidents. Due to the presence of moral hazard, this increase is relatively more pronounced in the case of injuries that are more difficult-to-diagnose.

3. Empirical model

3.1. Hypotheses

In our study of ex post moral hazard, we distinguish between difficult-to-diagnose and easy-to-diagnose injuries, based on a classification used by Dionne and St-Michel (1991). Let ΔMI_E and ΔMI_D represent variations in compensated days for easy and difficult minor injuries and ΔMA_E and ΔMA_D variations for easy and difficult major injuries. Table 1 summarizes these definitions.

***Table 1**: Variation in the Number of Days of Compensation Due to a Change in Coverage*

	Easy diagnosis (E)	**Difficult diagnosis (D)**
Minor injuries	ΔMI_E	ΔMI_D
Major injuries	ΔMA_E	ΔMA_D

Under asymmetric information, following a change in the insurance level, we should see:

- Case 1: When we have identical degrees of severity and different degrees of observability: $\Delta MI_E < \Delta MI_D$ and $\Delta MA_E < \Delta MA_D$.

- Case 2: When we have different degrees of severity and identical degrees of observability: $\Delta MI_E = \Delta MA_E$ and $\Delta MI_D = \Delta MA_D$.

Again, following Dionne and St-Michel, Table 2 classifies injuries according to their degree of severity and in terms of the difficulty of diagnosis.

***Table 2**: Classification of Injuries by Severity and Relative Difficulty of Diagnosis*

	Easy diagnosis (E)	**Difficult diagnosis (D)**
Minor injuries (MI_1)	MI_{E1}: Contusion	MI_D: Sprains and strains
Minor injuries (MI_2)	MI_{E2}: Friction burn	-
Major injuries (MA)	MA_E: Fracture	MA_D: Dislocation

3.2. Empirical specification

The empirical model includes the change in the insurance regime, the types of injuries and a set of control variables:

$$D_{it} = f\left(Z_{it}\right) = f\left(\text{ALPHA},\ \text{TYPE}_{it},\ X_{it},\ Y_{it}\right) \tag{3}$$

D_{it} is the severity of injury for individual i at time t. As in the rest of the literature, severity is proxied by the number of lost working days (see Fortin and Lanoie 2003, or Butler, 2013). ALPHA is a dummy capturing the change in the generosity of the workers' compensation regime; it is equal to 1 if the accident took place after 1995 and 0 otherwise. Theoretically, a rise in benefits reduces the opportunity cost of an accident for workers, inducing them to be less cautious, or to stay on workers' compensation longer after an accident; while it raises the opportunity cost of an accident for employers, inducing them to devote more resources to safety. The latter effect is more important when the degree of experience rating is high. Which effect dominates remains an empirical question; so far, the literature shows mainly that more generous insurance is associated with greater frequency and duration of workplace accidents. Many authors consider that this reflects a problem of *ex ante* moral hazard due to a suboptimal level of prevention activities (see Butler et al., 2013).

$TYPE_{it}$ is a vector of dichotomous variables identifying the type of injury as described in Table 2. X_{it} is a vector of control variables reflecting the demographic characteristics of the employee i at time t, while Y_{it} is a set of control variables related to industrial sectors and regions in which employee i is working at time t.

More specifically, to isolate the effects of ex post moral hazard associated to different types of injuries (Cases 1 and 2), we introduce interaction terms between ALPHA and different injury variables corresponding to the different diagnosis-severity cells found in Table 2. Finally, equation (3) can be rewritten as:

$$\begin{aligned} D_{it} &= B_0 + B_1 Alpha + \sum B_{2k} X_{it} + \sum B_{3k} Y_{it} + B_4 MI_{E1} + B_5 (Alpha.MI_{E1}) + B_6 MI_{E2} \\ &+ B_7 (Alpha.MI_{E2}) + B_8 MA_E + B_9 (Alpha.MA_E) + B_{10} MI_D + B_{11} (Alpha.MI_D) + \\ &B_{12} MA_D + B_{13} (Alpha.MA_D) \end{aligned} \tag{4}$$

As one can see, the coefficients B_5, B_7, B_9, B_{11} and B_{13} measure the effect of the change in insurance coverage on the number of lost working days depending on the difficulty of diagnosis. Thus, these coefficients are directly related to cases 1 and 2, and the moral hazard tests are based on the following Student's statistic test:

Case 1: $B_{11} > B_5$, $B_{11} > B_7$ and $B_{13} > B_9$.

Case 2: $B_{11} = B_{13}$, $B_5 = B_9$ and $B_7 = B_9$.

Among the control variables reflecting the demographic characteristics of the workers, X_{it}, we first have the variable FEMALE which is a dummy variable indicating if the injured worker is a female. Female workers tend to work in less hazardous occupations, so that they are injured less severely (see Lanoie, 1992). The variable AGE reflects the age of the injured victim. On the one hand, older workers are generally more risk-averse, which may reduce the severity of the accidents they have (Viscusi, 1986) but, on the other hand, ceteris paribus, they may take more time to recover from a given injury. EXPERIENCE refers to the number of years of experience of the injured worker, and MARRIED is related to his marital status. It is expected that more experienced workers are better at avoiding severe accidents, while married workers should be more risk-averse (Campolieti, 2001 and Butler et al., 2006). In the same vein, SCHOOLING is the number of years of education, and it is postulated that more educated workers are more careful, or occupy jobs that are less risky (Gerking et al., 1988).

Finally, the occupation of the worker is captured by five dummy variables: WHITE COLLAR, BLUE COLLAR, APPRENTICE, PERMANENT and CONTRACTUAL. As discussed above, the intrinsic nature of the task and the level of experience may influence the type of injury that may occur; it is thus expected that BLUE COLLAR, APPRENTICE and CONTRACTUAL workers are less able to avoid more severe accidents than PERMANENT and WHITE COLLAR workers.

In the vector Y_{it}, we first have a regional dummy variable to capture the fact that the accident risk and the occupational safety control may vary from one region to another. Because it is the most modern part of the country, the region where both employers and employees should be more sensitive to safety issues, it is expected that enterprises in GREAT TUNIS[7] will show a better accident record. We also include three dummy variables for firms belonging to RESOURCES, MANUFACTURING and CONSTRUCTION sectors to control for differences in the inherent riskiness of industries (the service industry is default). Finally, the UNEMPLOYMENT rate (at the industry level) is taken into account to control for differences in economic conditions. On the one hand, as suggested by Fortin et al. (1999) and Fortin and Lanoie (2003), it is expected that, when unemployment is high, workers may be tempted to stay longer on workers' compensation to avoid being on unemployment insurance which is less generous than WC. On the other hand,

[7] Great Tunis includes the following governorates: Tunis capital, Ben Arous, Manouba and Ariana.

when unemployment is high, workers may feel more vulnerable and may want to stay out of the labor market for shorter periods (Boden and Ruser, 2003).

3.3 Econometric Strategy

To estimate the reduced-form model given by equation (4), we examine the duration of workplace absences using hazard models. These models are frequently used in economics and industrial relations to examine events such as the time period between two jobs via a search model (Kiefer and Newmann, 2006), or the duration of workers'compensation claims (Campolieti, 2001).

We first consider standard parametric hazard models: The lognormal, the loglogistic and the gamma hazard models. The lognormal and the loglogistic are similar and tend to produce comparable results (Cleves et al., 2010). For the lognormal distribution, the natural logarithm of time follows a normal distribution; for the loglogistic distribution, the natural logarithm of time follows a logistic distribution.

The lognormal survivor and density functions for individual i at time t are:

$$S(t) = 1 - \Phi\left\{\frac{\log(t) - \mu}{\sigma}\right\} \tag{5}$$

$$f(t) = \frac{1}{t\sigma\sqrt{2\pi}} \exp\left[\frac{-1}{2\sigma^2}\left(\log(t) - \mu\right)^2\right] \tag{6}$$

where $\Phi(z)$ is the standard normal cumulative distribution function.

The lognormal regression is implemented by setting $\mu_i = Z_i^{'}B$ and treating the standard deviation, σ, as an ancillary parameter to be estimated from the data. Z_i is defined as in equation (3) above.

However, the loglogistic regression is obtained if Z_i has a logistic density. The loglogistic survivor and density functions are:

$$S(t) = \left[1 + (\lambda t)^{1/\gamma}\right]^{-1} \tag{7}$$

$$f(t) = \frac{\lambda^{1/\gamma} t^{1/\gamma - 1}}{\gamma\left(1 + (\lambda t)^{1/\gamma}\right)^2} \tag{8}$$

This model is implemented by parameterizing $\lambda_i = \exp\left(-Z_i^{'}B\right)$, and treating the scale parameter γ as an ancillary parameter to be estimated from the data.

Lognormal, and loglogistic models are sufficiently flexible for many datasets, but further flexibility can be obtained with the generalized gamma model. The three-parameter generalized gamma survivor and density functions are:

$$S(t) = \begin{cases} 1 - I(\gamma, u), \text{ if } k\rangle 0 \\ 1 - \Phi(z), \text{ if } k = 0 \\ I(\gamma, u), \text{ if } k\langle 0 \end{cases} \tag{9}$$

$$f(t) = \begin{cases} \dfrac{\gamma^{\gamma}}{\sigma t \sqrt{\gamma}(\gamma)} \exp\left(z\sqrt{\gamma} - u\right), \text{ if } k \neq 0 \\ \dfrac{1}{\sigma t \sqrt{2\pi}} \exp\left(-z^2/2\right), \text{ if } k = 0 \end{cases} \tag{10}$$

where $\gamma = |k|^{-2}$, $z = \text{sign}(k)\{\log(t) - \mu\} \times \dfrac{1}{\sigma}$, $u = \gamma \exp(|k|z)$; Φ is the standard normal cumulative distribution function and $I(\gamma, u)$ is the incomplete gamma function.

This model is implemented by parameterizing $\mu_i = Z_i^{'}B$ and treating the parameters k and σ as ancillary parameters to be estimated from the data.

The hazard function of the generalized gamma distribution is extremely flexible, allowing for many possible shapes, including as special cases the Weibull distribution when $k=1$, the exponential when $k=1$ and $\sigma=1$, and the lognormal distribution when $k=0$. The gamma model is, therefore, commonly used for evaluating and selecting an appropriate parametric model[8] for the data. The Wald or likelihood-ratio test can be used to test the hypotheses that $k=1$ or that $k=0$.

However, the standard hazard models presented above are often criticized because they ignore unobserved heterogeneity. The lognormal, the loglogistic and the gamma hazard models assume homogeneity: all individuals are subject to the same risks embodied in the hazard $\lambda(t)$ or the survivor functions $S(t)$. Covariates are the only source of heterogeneity. Ignoring unobserved heterogeneity may lead to a dynamic selection bias in the parameter estimates (Lancaster, 1990). For example, as time goes by, it is possible that workers who do not return to the labor market are those with an intrinsic bad health condition. If the analyst does not account for this unobserved heterogeneity, he may end up with the mistaken impression that the hazard declines through time.

Now we consider unobserved sources of heterogeneity that are not readily captured by covariates. One possible solution to the problem of unobserved heterogeneity is to introduce a random effect α in the hazard function, such that $h(t|\alpha)=\alpha h(t)$, where $h(t)$ is a nonfrailty hazard function. A survival model with unobservable heterogeneity is called a frailty model (Gutierrez, 2002). The frailty, α, is a random positive quantity and, for model identifiability, is assumed to have mean 1 and variance θ. For mathematical tractability, however, we limit the choice to either the gamma $\left(1/\theta, \theta\right)$ distribution or the inverse-Gaussian distribution with parameters 1 and $1/\theta$.

Specifying frailty (gamma) results in the frailty survival model:

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[8] When parametric models are nested, the likelihood-ratio or Wald test can be used to discriminate between them. This can be done for gamma versus lognormal. When models are not nested, however, these tests are inappropriate, and the task of discriminating between models becomes more difficult. A common approach to this problem is to use the Akaike information criterion (AIC). Akaike proposed penalizing each log-likelihood to reflect the number of parameters being estimated in a particular model and then comparing them. Here the AIC can be defined as AIC = -2(log-likelihood) + 2(c + p + 1) where c is the number of model covariates and p is the number of model-specific ancillary parameters. Although, the best-fitting model is the one with the largest log-likelihood, the preferred model is the one with the smallest AIC value.

$$S_\theta(t)=\left[1-\theta\log\left(S(t)\right)\right]^{-1/\theta} \tag{11}$$

Specifying frailty (inverse-Gaussian) results in:

$$S_\theta(t)=\exp\left\{\frac{1}{\theta}\left(1-\left[1-2\theta\log\left(S(t)\right)\right]^{1/2}\right)\right\} \tag{12}$$

These transformations allow us to obtain six frailty models: the lognormal with gamma frailty, the lognormal with inverse-Gaussian frailty, the loglogistic with gamma frailty, the loglogistic with inverse-Gaussian frailty, the gamma with gamma frailty, and the gamma with inverse-Gaussian frailty.

3.4 Description of the Data

The data in this study are taken from one main source, the *Caisse nationale de la sécurité sociale*. We have access to all the information concerning workplace accidents in Tunisia between 1993 and 2000. We excluded observations for fatal injuries and permanent disabilities because the duration variable, the number of working days lost, has no meaning in these cases. As a result, we have information about 145,377 injuries. We provide a description of our variables and some summary statistics in Table 3.

Table 3: *Descriptive Statistics*

Variable	Definition	Mean	S.D.
Dependent variable : D_i	**Average number of working days lost per worker**	6.31	5.2
Independent variables : Y_i			
GREAT TUNIS	Dummy Variable : equal 1 if a worker is located in Great Tunis, 0 otherwise	0.29	0.45
MANUFACTURING	Dummy variable for workers belonging to the manufacturing sector	0.54	0.49
CONSTRUCTION	Dummy variable for workers belonging to the construction sector	0.16	0.37
RESOURCES	Dummy variable for workers belonging to the extractive sector	0.018	0.13
UNEMPLOYMENT	Unemployment rate by industry	15.54	0.25
Workers characteristics : X_i			
AGE	Number of years	35.31	8.55
EXPERIENCE	Number of years of experience	5.57	7.25
SCHOOLING	Number of years of education	7.16	2.4
FEMALE	Dummy variable for female workers	0.12	0.32

MARRIED	Dummy variable for married workers	0.55	0.49
WHITE COLLAR	Dummy variable for administrative workers	0.027	0.16
BLUE COLLAR	Dummy variable for blue collar workers	0.34	0.47
APPRENTICE	Dummy variable for apprentice workers	0.031	0.17
PERMANENT	Dummy variable for workers with a permanence status	0.46	0.49
CONTRACTUAL	Dummy variable for contractual workers	0.18	0.39
Other variables			
ALPHA	Time dummy variable equal to 1 if the accident took place in 1995-2000 inclusively	0.73	0.73
MI_{E1}	Dummy variable for minor injuries with easy diagnosis (contusion)	0.042	0.202
MI_{E2}	Dummy variable for minor injuries with easy diagnosis (friction burn)	0.029	0.16
MI_d	Dummy variable for minor injuries with difficult diagnosis	0.063	0.24
MA_e	Dummy variable for major injuries with easy diagnosis injuries	0.09	0.28
MA_d	Dummy variable for major injuries with difficult diagnosis	0.036	0.18

S.D. stands for standard deviation.

Table 3 shows that the average duration is 6.3 days and that most workers covered in our sample are men (88%) with a permanence status (46%) in the manufacturing sector (54%). Only 2.7% of victims are white collar workers. Furthermore, just 29% of compensated workers are located near Tunis City, while 73% of observed accidents took place after 1995.

4. Empirical results

Table 4: *Hazard models estimates*

Dependent variable: The severity of accidents									
Independent variables	**Loglogistic (1)**	**Lognormal (2)**	**Gamma (3)**	**Lognormal (4) (Frailty gamma)**	**Lognormal (5) (Frailty invgauss)**	**Loglogistic (6) (Frailty invgauss)**	**Loglogistic (7) (Frailty gamma)**	**Gamma (8) (Frailty gamma)**	**Gamma (9) (Frailty invgauss)**
ALPHA	-0.02720***	-0.0274059***	- 0.017512***	-0.0205822***	-0.0168741***	-0.0207778***	-0.0235481***	-0.0174698***	-0.0125657**
MI$_{D}$	0.0135794	0.0193521	0.031432*	0.0247239	0.0296693*	0.0181017	0.0157621	0.0283128**	0.0588717***
MI$_{E1}$	-0.0163646	-0.0149443	- 0.0004244	-0.0064583	-0.0014662	-0.0097931	-0.0125057	-0.0050383	0.0050367
MI$_{E2}$	-0.0005588	-0.0088387	-0.0161181	-0.0099568	-0.0150274	-0.0032062	-0.0010514	-0.0130998	-0.0182713
MA$_{D}$	0.1676603***	0.1460957***	0.1242734***	0.1465879***	0.140191***	0.1780831***	0.1739266***	0.1340169***	0.0173185
MA$_{E}$	-0.029469***	-0.0278225**	-0.0198747	-0.023318*	-0.0196959	-0.0236373*	-0.0264118*	-0.0199224*	-0.0164742
ALPHA*MI$_{D}$	-0.073064***	-0.0813954***	-0.1020747***	-0.0914988***	-0.0996779***	-0.0801685***	-0.0765805***	-0.0921005***	-0.1263308***
ALPHA*MI$_{E1}$	0.0054027	0.0060607	-0.0091337	-0.004407	-0.0095262	-0.0034519	0.0000992	-0.0052321	-0.0167657
ALPHA*MI$_{E2}$	-0.0044263	0.0119738	0.0048376	-0.001549	-0.0008445	-0.0165095	-0.0128023	0.0002115	-0.0076118
ALPHA*MA$_{D}$	-0.299197***	-0.2756736***	-0.282***	-0.2966993***	-0.2997523***	-0.3230351***	-0.3136275***	-0.2757591***	-0.1690638***
ALPHA*MA$_{E}$	0.0368207**	0.034763*	0.0284132	0.031675*	0.0284761*	0.0313204*	0.034063*	0.0270275*	0.0228017
GREAT TUNIS	0.0728367***	0.0693692***	0.109272***	0.0975796***	0.110323***	0.0925878***	0.0847776***	0.0934029***	0.1115149***
MANUFACTURING	0.0111267*	0.0116843*	0.0068873	0.0081006**	0.0063912**	0.0077072*	0.0091622*	0.0069836	0.0080713
CONSTRUCTION	-0.0028951	-0.0025234	-0.0122328	-0.0097479	-0.0135676**	-0.0096688*	-0.0066319	-0.0119132**	-0.0075662**
RESOURCES	0.0218105	0.0181214	0.0121279	0.0159639	0.0128932	0.01925	0.0208096	0.0116575	0.008328
UNEMPLOYMENT	0.0250665***	0.0258545***	0.018445*	0.020228**	0.0173294*	0.0194641**	0.0219102**	0.0177282**	0.0056*
AGE	-0.0000377	-0.0000279	0.0000322	80.54e-06	-0.0000308**	-0.0000146**	-70.77e-06	-1.22e-07	-0.000142**
EXPERIENCE	0.0007739	0.0009378*	0.000483	0.000546**	0.0004182**	0.0004358*	0.0005617*	0.0005228	0.001532***
SCHOOLING	0.0004736	0.0010669	0.0004622	0.0003297**	0.0002281**	-0.0001185	0.0000765*	0.0004186	0.000287**
FEMALE	0.0269843***	0.0228576***	0.0376421***	0.0349276***	0.0392928***	0.036211***	0.0327362***	0.0320475***	0.0247027***
MARRIED	-0.001112	-0.0012769	-0.0007092	-0.0008243	-0.0006731	-0.0008523	-0.0009244	-0.0011606	-0.0004764
WHITE COLLAR	0.0442344***	0.0311677*	0.0550807***	0.0537588***	0.0600226***	0.062541***	0.0557196***	0.051245***	0.0483043***
BLUE COLLAR	-0.0290***	-0.0327908***	-0.0503317***	-0.0428123***	-0.0498031***	-0.0355954***	-0.0325455***	-0.0413526***	-0.0604229***
APPRENTICE	-0.0249408	-0.0152777	-0.0494***	-0.0439252***	-0.0538922***	-0.0475399***	-0.0389176**	-0.0418587***	-0.05011***
PERMANENT	0.0003668	0.0006607	-0.001602	-0.0009624	-0.0016101	-0.0009375	-0.0004083	-0.0010792	-0.0080737

CONTRACTUAL	-0.0031723	-0.0020275	-0.0016689	-0.0023893	-0.0019841	-0.0033863	-0.0034216	-0.0017711	-0.0018589
CONSTANT	1.25586**	1.296341**	1.150513**	1.241201**	1.176433**	1.222633**	1.241445**	1.179873*	1.236251*
Gamma	0.5214146***	-	-	-	-	0.4263979***	0.4683902***	-	-
Sigma	-	0.90***	0.837***	0.7462742***	0.6504151***	-	-	0.8390984***	0.5006***
Kappa	-	-	-0.583***	-	-	-	-	-0.923357***	0.348***
Theta (θ)	-	-	-	0.2771134***	0.7842554***	0.3198425***	0.1324676***	0.0174055*	3.193***
LOG-LIKELIHOOD	-162749.92	-160714.39	-158139.97	-159380.99	-158407.93	-161922.75	-162321.94	-161,629	-157,539.75
Observations	145,377	145,377	145,377	145,377	145,377	145,377	145,377	145,377	145,377
Likelihood-ratio test: θ = 0	-	-	-	X_2 (1) = 2666.79	X_2 (1) = 4612.92	X_2 (1) = 1654.33	X_2 (1) = 855.95	X_2 (1) = 0.00	X_2 (1) = 1200.44

*** P-value < 0.01, ** P-value < 0.05, * P-value < 0.1

Table 4 presents our empirical results. The first three columns present our estimates using standard parametric hazard models: lognormal, loglogistic and gamma. Columns (4) to (9) present estimates when we account for unobserved heterogeneity (using gamma or inverse-Gaussian distributions). One should note that, with hazard models, the estimated coefficients measure the impact of the independent variable on the rate of exit from WC. As a first appreciation, it is comforting that many coefficients are significant and robust across specifications.

Among the three first specifications, as expected, the lognormal and the loglogistic estimates are similar and tend to produce comparable results. The gamma model provides the best fit with the largest log likelihood, and is preferred using the AIC criterion[9].

All hazard models with heterogeneity except for model (8) show a statistically significant level of unobservable heterogeneity because the P-value for the likelihood-ratio test of the null hypothesis (H_0: $\theta = 0$) is virtually zero in all cases. The results are similar with respect to the choice of frailty distribution, but the gamma model with inverse-Gaussian frailty produces a slightly higher likelihood[10]. This leads us to conclude that the gamma model with inverse-Gaussian frailty is our "preferred" specification (column 9). Therefore, the tests presented in Table 5a and 5b are made using this specification.

Concerning our main variables of interest, Table 5a depicts that the coefficients associated to the product of ALPHA and injuries with difficult diagnosis are statistically larger than those related to injuries with easy diagnosis. Hypothesis of occurrence of ex post moral hazard (Case 1) is always accepted at 95% confidence level. This means that, as insurance coverage increased in

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[9] AIC (lognormal) = 321484.8; AIC (loglogistic) = 325555.8 ; AIC (gamma) = 316337.9. The Wald test of the hypothesis that k = 0 (test for the appropriateness of the lognormal) is reported in Table 4 (Statistic = -0.583***). The P-value is 0.000, suggesting that lognormal model is inadequate for these data. In addition, since the lognormal and the gamma models are nested, the likelihood ratio test (X_2 (1) = 5148.84 and a P-value of 0.0000) favor the gamma model. Testing the hypothesis that k = 1 (test for the appropriateness of the Weibull model) yields a X_2 (1) = 39989.37. This suggests that the Weibull model is not appropriate for our data.

[10] AIC (lognormal with gamma frailty) = 318820; AIC (lognormal with inverse-Gaussian frailty) = 316,873.9; AIC (loglogistic with gamma frailty) = 324,701.9; AIC (loglogistic with inverse-Gaussian frailty) = 323,903.5; AIC (gamma with gamma frailty) = 323,318; AIC (gamma with inverse-Gaussian frailty) = 315,139.5.

Tunisia, days spent on difficult-to-diagnose claims rose significantly more than did claims with easy diagnosis. This is consistent with what has been observed in Dionne and St-Michel (1991) and Autor, et al. (2012).

***Table 5$_a$*: Test** *of moral hazard (Case 1)*

H0	H1	Tc	Decision
$B_{11} = B_5$	$B_{11} > B_5$	3.28	Reject of H0 (95%)
$B_{11} = B_7$	$B_{11} > B_7$	3.29	Reject of H0 (95%)
$B_{13} = B_9$	$B_{13} > B_9$	6.16	Reject of H0 (95%)

***Table 5$_b$* :** *Test of moral hazard (Case 2)*

H0	H1	Tc	Decision
$B_{11} = B_{13}$	$B_{11} \neq B_{13}$	1.04	Reject of H1 (95%)
$B_5 = B_9$	$B_5 \neq B_9$	1.24	Reject of H1 (95%)
$B_7 = B_9$	$B_7 \neq B_9$	0.87	Reject of H1 (95%)

In addition, table 5b shows that the second hypothesis (case 2) is confirmed. We expected that different categories of severity with identical degrees of observability would be influenced in the same way by the change in insurance coverage. These results are also consistent with those in Dionne and St-Michel (1991).

Furthermore, the coefficient of ALPHA is negative and significant. As discussed in our analytical section, this suggests the presence of *ex ante* moral hazard. It is noteworthy that, in Dionne and St-Michel, this coefficient was not significant. In other words, we seem to detect the presence of *ex ante* moral hazard in addition to *ex post* moral hazard. This could mean that, overall, moral hazard problems are more important in developing countries than in industrialized ones[11].

[11] For the sake of doing a strict comparison with Dionne and St-Michel's results, we also estimated equation (3) with OLS and the nature of our results was qualitatively the same. Complete results are available upon request.

In column (9), the estimated coefficients of most control variables are of the expected sign and many are significant. As discussed earlier, the variable AGE comes with a negative sign which could suggest that, everything else being equal, older workers take more time to recover. As expected, more experience workers, white collars, female and more educated workers have shorter recovery periods, while blue collars and apprentices have longer periods. The workers in the construction sector have more severe accidents than those in the default group (service industry).

As expected, the workers in the GREAT TUNIS area have lower duration of accidents than those in the less urban regions. Finally, ceteris paribus, the severity of accidents is lower as the industrial unemployment rate increases, which suggests that workers could feel more vulnerable when the unemployment rate is high, giving them more incentive to come back rapidly in the labor market after an accident.

Conclusion

In this paper, we have analyzed the problem of ex post moral hazard associated with a more generous workers'compensation regime in Tunisia. To our knowledge, this is the first study on moral hazard associated with WC in a developing country. Our approach was based on that developed by Dionne and St-Michel (1991) who tackle the question by looking at the impact of more generous indemnity payments on the duration of injuries which are hard-to-diagnose, thus involving more important information asymmetry. In particular, we find that more generous insurance is associated with longer recovery periods, and that this phenomenon is more acute for hard-to-diagnose injuries.

Our results also suggest that, overall, the moral hazard problems detected with the Tunisian data were more important than what Dionne and St-Michel found with Canadian data. This could mean that developing countries are probably more exposed to moral hazard than industrialized countries with detrimental consequences on productivity and competitiveness.

More attention should be devoted to this problem by the academic community and by governments. In particular, in light of our results, governments may want to put more efforts to promote accident prevention in the first place, or to develop better auditing procedures for claims in the case of injuries which are hard-to-diagnose.

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