Health conditions and injuries: a comparison of their effects on employment and earnings in France

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Abstract

This paper investigates whether health shocks such as chronic and/or severe diseases compared with injuries have a causal impact on employment trajectories, employment quality and related earnings in France. We use the "Sante Itinéraires Professionnels"a survey conducted in France in 2006-2007 about 14,000 people aged from 24 to 70. This survey is a retrospective one which interviews people from the origin of their career. For each interest variable (either chronic health conditions or injuries) we use the propensity score matching method in order to evaluate the impact of diseases and accidents on employment trajectories, employment quality and related earnings.

JEL Classification: I10, J20, J31

1. Introduction

Health shocks and injuries (such as road or domestic accidents) induce socio-economic costs. The socio economic costs include long-term care, production loss and welfare loss. Concerning employment, it is difficult to know how deep or how long the consequences of chronic illness or injuries are, and how different the impact is on the ability to work and related earnings.

The goal of this paper is to investigate whether there exists a causal effect of significant chronic illnesses and injuries on employment (professional trajectories and employment quality) and related earnings. Injuries may be considered for a large part as random shocks. It is also the fact for some diseases which are unrelated to a deliberate individual behaviour.

Concerning the relationship between health, earnings and employment, a large number of studies reveal an impact of health on earnings and employment (see Currie, Madrian, 1999 for a survey). The results they obtain depend partly on the type of samples used, the health measures retained and the econometric methodology used. A current result is that health has a greater effect on hours of work than on wages (for instance, Chikiros, Nestel, 1981, 1985 ; Chirikos, 1993 ; Mitchell,

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Burkhauser, 1990). The effect on health on persistent or long-term unemployment has been less studied. A recent paper by Haan and Myck (2009), shows that there are persistent dynamics of both bad health and unemployment. Such results are also obtained by Lindeboom, Llena-Nozal and van der Klauw (2006). The authors use the data from the British National Child Development Study (NCDS) which is a panel who follows people from birth until the age of 42. Using the health shock as an instrumental variable they show that the onset of a disability at age 25 causally reduces the employment rate at age of 42 by 21 percentage points. The authors also show that early childhood conditions are of great importance in explaining adult health and socio-economic outcomes. "Those who have experienced bad conditions during early childhood during early conditions have higher rates of health deterioration during childhood are more likely to become non-employed and suffer from longer spells of non-employment during the course of life". Moreover, more recently, an important literature takes into account the early childhood conditions on adult health (Case, Fertig, Paxson (2005) ; Wadsworth, Butterworth (2006) ; Trannoy, Tubeuf, Jusot, Devaux (2008)).

However, the issue of the health measure that is used may be important regarding the causal relationship between health and employment or earnings. Generally, the previous studies use one or more of the four following measures: 1/ self rated health, 2/ functional limitations of daily activities, 3/ limitations of ability related to work, 4/ chronic or severe illness or diseases. This measures or indicators of health may be completed by other indicators like 5/the use of medical care, 6/ the use of mental health or depression scales, 7/ the weight, size and body mass index (BMI).

If a number of studies show that the self-rated health measures are well correlated with mortality (see for instance, Idler, Benyamini, 1997) and with the consumption of medical care, the self-rated measures do not always give a good summary of the severity of diseases (Lanoë, 2005).

The main problem in the study of the link between health and work or employment, related to the use of self rated health measures, is not due to the fact that this measure is not correlated to the underlying health state, since it affects the status on the labor market, but rather that the measurement error does not necessarily result from a random process. Their could be a "justification bias": the people who diminish their work time or who exit from the labor market are more likely to declare bad health, functional limitations or limitations related to work. Therefore, the studies of the impact of health on work and employment can be improved when several indicators or measures of health conditions are used.

Concerning the injuries, less studies have been made. We consider here two kinds of injuries: domestic injuries and road injuries. In France, the road injuries and domestic injuries are reported by two and distinct procedures. Concerning the road injuries, the total cost is estimated billions €25, that is 1.3% of the GDP. Moller Dano (2006) report that "road accidents killed over 40 000 people in the

European Union in 2000, and more than 1.3 million road accidents involved personal injury" (p. 955). In this study, she investigates whether road injuries ("unexpected shocks") have a causal impact on disposable income, earnings, employment and public transfer income in Denmark. She uses the propensity score matching method. She finds that older injured persons and injured persons in the lower part of the income distribution have significantly lower disposable incomes than older and low-income non-injured persons. In the short term as well as in the long term, the employment rates are lower for the injured men than for the non-injured persons belonging to the control group. There is no effect for women. Moreover, reduced earnings are found for men in general and for the elder women.

In this paper, we compare the impacts of health conditions measured by different chronic and severe diseases with the impact of injuries on employment trajectories and employment quality. We use the "Sante Itinéraires Professionnels" Survey run in France in 2006-2007 about 14,000 people aged from 24 to 70. This survey is a retrospective one which interviews people from the origin of their career. It contains questions about subjective health (self rated health but also diseases with a detailed report of the kinds of disease and symptoms, functional and activity limitations, pains, sleep troubles, mental health- measured by Mini questionnaire- sequels) and the employment trajectories (type of contract, working time –hours of work- duration of employment, change of employment, unemployment and it spell) and the related earnings.

This paper is organized as follows: the second section presents the data and presents some sample statistics. Section 3 explains the methodology used to identify the effects of health or accidents on the professional career. The fourth section presents the results and discusses them. The last section concludes.

2. The data

Identification of chronic or severe illness and injuries

The scope of the analysis is restricted to the people aged from 19 to 55. In France, after 55, people may benefit from legal dispositions to exit labour market due to handicap. We also exclude of the analysis the retired and the people who suffer from professional disease insofar our aim is to identify the way health conditions may affect employment and working conditions and not the reverse causality.

Chronic or severe illness

In order to identify the chronic diseases we report on epidemiologists views of diseases causing limitations (see WHO, IDC) and on the French administrative classification of severe diseases (the so-called "affections de longue durée"). In the SIP survey, the data set is very detailed about the type of diseases from which people suffer, in a declarative sense.

We have retained: chronic cardio-vascular diseases, cancers, deafness, chronic hearing impairment (tinnitus), severe or chronic lung diseases, severe or chronic liver diseases, severe or chronic rheumatics, diabetes, severe or chronic eye disorders (with difficulties impossible to correct) ; blindness, severe or chronic psychiatric disorders, epilepsy, addictions, AIDS or other severe diseases.

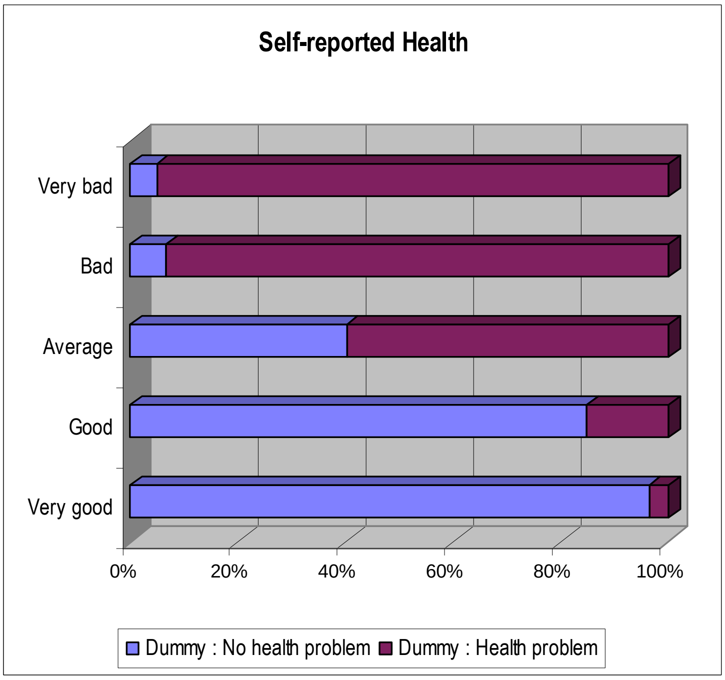
Sample definition

Age : 19 to 55 years old
Excluding retired workers
Excluding work related-health problems
Including only chronic diseases

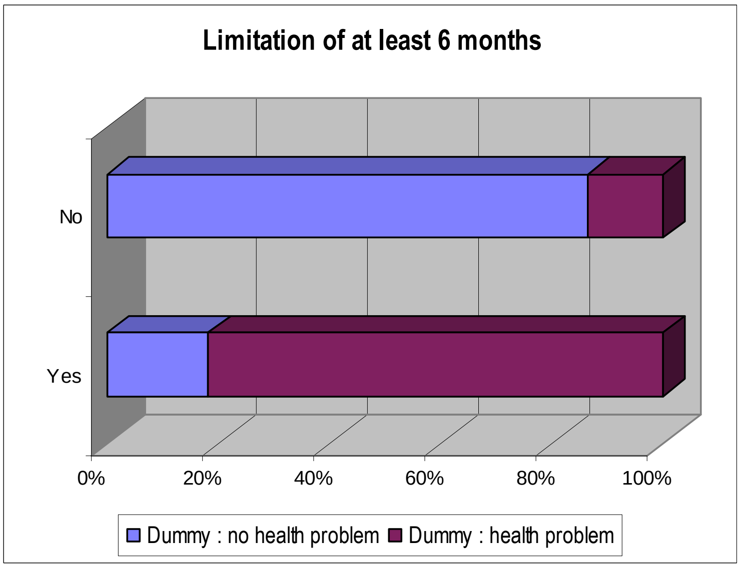
We keep the following diseases (SCOD variable)

2, 4, 5,6 : cardiovascular diseases
9 : cancers
11, 12 : lung diseases
16,17 : deafness, tinnitus
20 : liver disease
23 : slipped disc
28 : bones and articulation diseases31 : diabète
35 : eye troubles difficult or impossible to correct
37, 38 : severe mental illness
42 : epilepsy
48, 49 : addiction to alcool and other products (except tobacco)
50 : often HIV

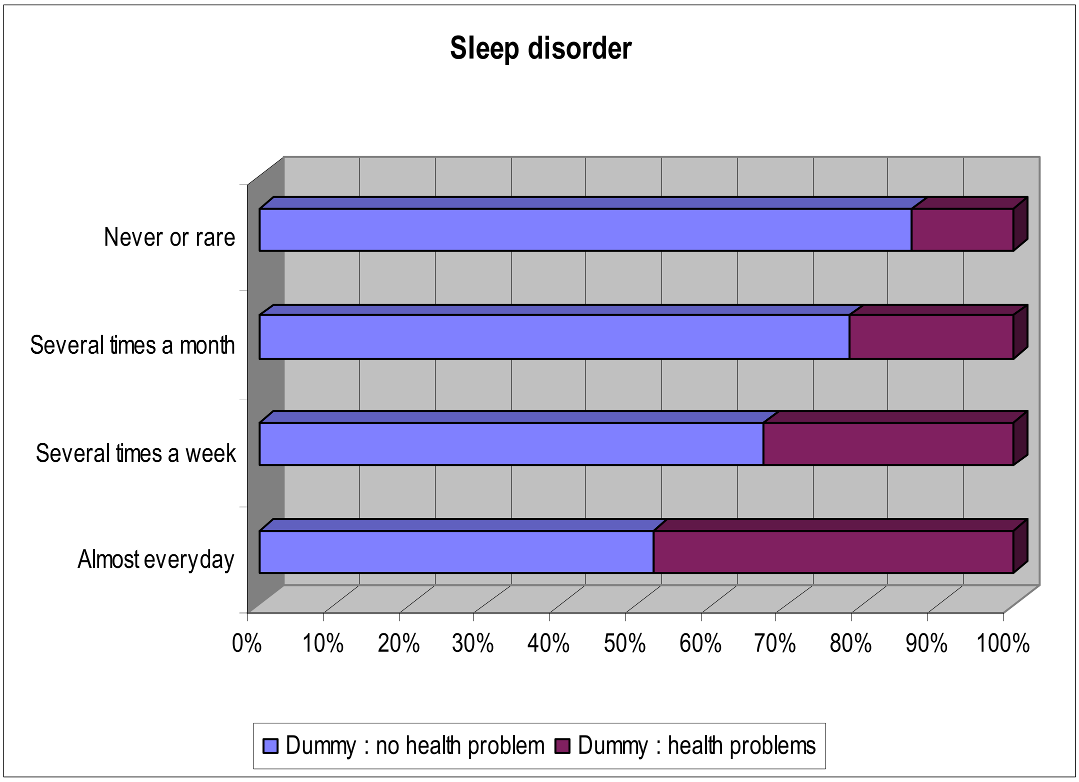
The indicator we use is a binary variable indicating the presence or absence of such a disease. In order to assess its quality, we compare it to the other health indicators available in the survey. First, we examine the relation between this indicator and the self-rated health measure. The correlation is excellent. People that have a health problem according to our indicator almost all report a bad or a very bad health, and the reverse when our indicator reports no health problem.



The second health indicator available in the survey refers to the existence of a health limitation that has lasted at least 6 months. The correlation is also very good.



Lastly, we examine the correlation of our indicator with the measure indicating the presence of sleep disorders. We also find a strong correlation.



Overall, our dummy indicator is strongly correlated with the standard health indicators.

Injuries

To take into account the accidents, we use the part of the questionnaire related to the existence of an accident occurring either during the house-workplace trip either outside the workplace area (then including car injuries and domestic accidents). About 10% of the people declare an accident. We exclude the workplace accidents because a reverse causality can be associated to the explanation of their link to employment (work conditions may influence the occurrence of accidents and accidents may impact the participation to job market or employment trajectories)

Descriptive statistics concerning health

Table 1 provides some sample statistics, and performs a comparison of the people with and without health problems. This Table allows for detecting some potential selection biases, that is the performance differences that are not related to the health status but to the fact that the two groups differ in some exogenous variables. More precisely we find that the people suffering from health problems are older (4 years) than the others, a point that must be corrected in the estimation, in order to avoid attributing to health the effects that come from age. Similarly, we find that the people suffering health problems achieved a lower education level than the others. We also find “significant” effects on the labor market: people with health problems more often new long run unemployment and inactivity and their wage distribution is shifted to the left (i.e. presents lower values) compared to the people without health problems. However, one should be careful about the latter result: since the people suffering from health problems also achieved a lower education level, so that the effect on the wage distribution could well not be attributed to a bad health. In order to separate the effects of health from the effects of the other variables, we will need to introduce several control variables. In order to determine which control variables we should include in our regressions we proceed in the following way: we keep the exogenous variables correlated with the probability to have a health problem. Indeed, if some exogenous variables are not correlated with the health condition they cannot cause a selection bias. In order to get the list of these variables, we run a Probit regression of the health dummy on our exogenous variables, and keep the ones that are significant. But we will also use these probabilities to match the people with and without health problems.

3. Methodology

We want to measure the effect of a bad health (or of an accident as characterized above) on the professional career. Therefore we should evaluate the difference between the performance that an individual achieves with a bad health and the performance the same individual would have achieved with a good health. The latter quantity is called the counterfactual. There are many ways to estimate a counterfactual. In this paper, we consider two families of methods: standard regression analysis (“naive regression estimators”) and weighting methods (“evaluation estimators”).

Let $y_{1,i}$ the performance of individual *i* with a bad health and $y_{0,i}$ the performance with a good health. The evaluation problem comes from the fact that we cannot observe both quantities at the same time. Either we observe y_{1i} when the individual has a bad health or we observe y_{0i} when (s)he does not. The observable data is therefore:

$$y_i = (1 - T_i) y_{0i} + T_i y_{1i} \text{ with } T_i = \begin{cases} 1 & \text{with a bad health} \\ 0 & \text{otherwise} \end{cases}$$

Naive regression methods

The methods in this section are useful mostly because they allow assessing the biases associated to them. The simplest method is the naïve estimator that takes the difference between the average performance of the individuals with a bad health and a good health. Technically this reduces to perform an OLS regression of the performance on the intercept and a bad health dummy variable (equal to 1 for a bad health, 0 for a good health). The OLS coefficient of the bad health dummy variable gives the difference of the mean performances in both groups:

$$\hat{c} = \frac{1}{N_1} \sum_{i \in I_1} y_i - \frac{1}{N_0} \sum_{i \in I_0} y_i$$

where I_1 is the index set of the bad health individuals (number: N_1), and I_0 the index set of the good health individuals- (number N_0).This is the « naive » estimator. A second method extends the previous model by adding control variables X_i into the previous regression. The model becomes:

$y_i = a + X_i b + c T_i + u_i$, where u_i is the usual disturbance, uncorrelated with the explanative variables.

From this model, we derive two quantities: 1/ for $T_i = 0$, we obtain an expected average performance $E(y_i | T_i = 0) = a + X_i b$, and 2/ for $T_i = 1$, we get the expected average performance $E(y_i | T_i = 1) = a + X_i b + c$. This implies that the effect of a bad health for the individual *i* is equal to:

$$E(y_i | T_i = 1) - E(y_i | T_i = 0) = c.$$

Compared with the naïve estimator, this regression allows dropping from the evaluation the part that is attributable to the control variables X_i. But, strictly speaking, this estimator is not fully consistent with the evaluation problematic *even* when there is no selection bias. A third regression method is more rigorous. We assume that there are two equations corresponding to each of the potential outcome, so that:

$$y_{0i} = a_0 + X_i b_0 + u_{0i} \text{ and } y_{1i} = a_1 + X_i b_1 + u_{1i},$$

And the observable performance is :

$$y_i = (1 - T_i) y_{0i} + T_i y_{1i} = (1 - T_i)(a_0 + X_i b_0 + u_{0i}) + T_i (a_1 + X_i b_1 + u_{1i}),$$

After some simplification, we get:

$$y_i = \beta_0 + X_i \beta_1 + T_i \beta_2 + T_i X_i \beta_3 + u_i,$$

With $\beta_0 = a_0$, $\beta_1 = b_0$, $\beta_2 = a_1 - a_0$, $\beta_3 = b_1 - b_0$, $u_i = (1 - T_i) u_{0i} + T_i u_{1i}$

which implies that one should estimate a model with the cross product of the explanative variables and the bad health dummy. Moreover, if the variables X_i are centred, we can show that the coefficient of the bad health dummy, β_2, measures the average effect of a bad health on the performance.[3] The structure of this model also implies that the disturbance of the model is heteroskedastic since the disturbance is different depending on $T_i = 0$ or $T_i = 1$. We account for this property in our estimations.

Evaluation methods

The "evaluation methods" are the most important in this paper since the naive regression methods do not account for the fact that the individuals are not comparable in the bad health and good health groups. We follow the propensity score approach initiated by Rosenbaum and Rubin (1983, 1985) and surveyed in Lee (2005) and Rubin (2006). The usual parameter of interest in the literature is the average treatment on the treated (ATT) defined as:

$$ATT = E(y_1 - y_0 | T = 1) = E(y_1 | T = 1) - E(y_0 | T = 1)$$

But the ATT cannot be identified without further assumptions, since $E(y_0 | T = 1)$ is not observable. The assumption of random selection is not satisfied in our study because there are a number of characteristics which may influence both the risk of injuries, some risks of diseases and trajectories employment. Conditioning on a vector of covariates X, the ATT becomes:

$$ATT(X) = E(y_1 - y_0 | T = 1, X) = E(y_1 | T = 1, X) - E(y_0 | T = 1, X)$$

where X is a vector of characteristics not affected by the treatment. In this first draft we consider matching on observables in order to identity a causal treatment effect on the treated (see for instance, Deheija and Wahba, 2002). The ATT may be identified by introducing the Conditional Independence Assumption assumption:

$$E(y_0 | T = 1, X) = E(y_0 | T = 0, X)$$

[3] The structure of this model also implies that the disturbance of the model is heteroskedastic since the disturbance is different depending on $T_i = 0$ or $T_i = 1$. We account for this property in our estimations.

This assumption implies that conditioning on X, the expected potential outcome in the case of non-treatment is the same for both treated and non treated groups. Thus the observed outcome for bad health people may be used to measure the potential outcome for good health people conditional on the characteristics X.

When the set of observed characteristics is large enough, matching should enable to consistently estimate the causal effects of a bad health on employment trajectories, employment quality and related earnings. Rosenbaum and Rubin (1983) show that instead of conditioning on a high dimensional X, control for covariates can be obtained by controlling for a real-valued function of X, P(X), called the propensity score, defined as the probability to get the treatment (i.e, to have a bad health, in our study). This implies that:

$$E(Y_0 \mid T=1, P(X)) = E(Y_0 \mid T=0, P(X)),$$

The intuition of this result is the following : if two individuals have the same probability to have a bad health, and the first individual does have a bad health while the other has not, then the allocation of bad health can be considered as random between these two individuals, and we can use the second individual as a counterfactual for the first individual.

Last, in order to ensure that our estimators have a relevant empirical content, we need to account for a last constraint: the individuals in the treatment group and in the control group must have *similar probabilities* to get the treatment. Therefore we make all our estimations on the *common support* of the treatment probabilities. More precisely, once we have estimated the probabilities to have a bad health, we define the supports of the probabilities on the treated and not treated groups by the 1^{st} and 99^{th} percentiles (to avoid outliers). Then, we take the intersection of these two supports. This implies that the comparisons can only be made on a part of the sample: the individuals that have probabilities of a bad health close to 0 or 1 must be excluded from the evaluation. In practice, we find that between 86% and 96% of the individuals can be compared, depending on the sub-sample we consider (some performance variables are defined on subsets of the data only, so that this rate can differ).

There are several ways to apply the propensity score methodology: the most common are kernel matching and weighting. We retained the second methodology in this paper. One reason is that kernel matching is often applied with non optimal windows and non optimal kernels, and requires the use of the bootstrap for evaluating the standard errors, therefore leading to less accuracy and a much higher computing time.[4] The weighting approach uses the same assumptions than kernel matching, but

[4] A previous study on the R&D tax credit (Duguet, 2008) finds that (gaussian) kernel matching with a rule-of-thum window gives similar results but with a higher variance. In practice, this could be fixed by taking an

merely expresses the non observable sample moments by their observable counterparts, and replaces them by the corresponding empirical moments. We get the following results:

a/ Effect of the treatment on the not treated :

$$c_0 = \frac{1}{N^c} \sum_{i=1}^{N^c} \left(\frac{N_0^c}{N^c} \right)^{-1} y_i \left(\frac{T_i}{\pi_i} - 1 \right)$$

b/ Effect of the treatment on the treated :

$$c_1 = \frac{1}{N^c} \sum_{i=1}^{N^c} \left(\frac{N_0^c}{N^c} \right)^{-1} y_i \left(\frac{T_i - \pi_i}{1 - \pi_i} \right)$$

c/ Effect of the treatment on the whole population :

$$c = \frac{1}{N^c} \sum_{i=1}^{N^c} y_i \left(\frac{T_i - \pi_i}{\pi_i (1 - \pi_i)} \right)$$

Where π_i is the value of the propensity score for the individual *i*, N^c the number of individuals in the common support, N_0^c the number of not treated in the common support and N_1^c the corresponding number of treated individuals. In practice, we do not know the exact value of π_i, so that we replace it by a consistent estimators. In our application, we use a Probit model estimated by the maximum likelihood method, and get a prediction $\hat{\pi}_i$ of the propensity score, which is used for the evaluation. This clearly affects the variance of the evaluation parameters in the following way.

All our estimators can be written on the following form :

$$\hat{\theta} = \frac{1}{N^c} \sum_{i=1}^{N^C} y_i g_i \left(\hat{b} \right)$$

where $\hat{b}$ is the estimated parameter from the Probit model. Using the delta method, we can estimate the variance of our estimate by :

$$\hat{V}\left(\hat{\theta}\right) = \frac{1}{N^c} \sum_{i=1}^{N^c} \left(\hat{\varphi}_i - \overline{\hat{\varphi}} \right)^2$$

adpatative Epanechnikov kernel and cross validation on the full sample. This is on the agenda for a future version of the paper.

with

$$\hat{\varphi}_i = y_i g_i\left(\hat{b}\right) + \frac{1}{N^c}\sum_{i=1}^{N^c}\left[y_i \frac{\partial g_i}{\partial b'}\left(\hat{b}\right)\right] J_1\left(\hat{b}\right)^{-1} \sqrt{N^c}\, s_i\left(\hat{b}\right)$$

where :

$$J_1(b) = E\left[-\frac{\partial^2 \ln f}{\partial b \partial b'}\left(T|X,b\right)\right],\ s_i(b) = \frac{\partial \ln f\left(T_i|X_i,b\right)}{\partial b},$$

and

$$\ln f\left(T_i|X_i,b\right) = T_i \ln \Phi(X_i b) + (1-T_i)\ln(1-\Phi(X_i b)).$$

Notice that these formulas are valid for any binary model estimated by the maximum likelihood method, provided that one replaces $\Phi(X_i b)\ \Phi$ by $1-F(-X_i b)$ where F(.) is the cdf of the disturbance of the new model (or by $F(X_i b)$ if the distribution is symmetric).

4. Results

Probit estimates

We first focus on the propensity score, defined as the probability to get a health problem. Table 2 reports the probability to fall sick for women. As expected, age is a significant variable. Compared with a women younger than 27, the probability to get sick increases by 6 points between 28 and 36 (these 6 points can be added to the baseline probability), by 9 points from 37 to 45, and by 16 points over 46 years old. The education level is positively correlated with health: the higher the education level, the lower the probability to get a health problem. We also find that the childhood events play a significant role : a woman that had been separated from her family has a higher probability to get health problems (+4.6 points). Conversely, a women educated by her mother has less chances to get health problems that the other women (-9.5 points). Heredity, broadly defined, seems to play a role too : when the parent had serious health problems, a woman has more chance to also get health problems (+8.8 points). We also find residential effects: compared to the Paris area, the probability to be sick stronger on the Riviera (PACA), Midi-Pyrénées, Lorraine and Franche Comté. In is lower in Limousin. These effects are likely to reflect “sorting” effects well known in the spatial economics literature. For instance, there is a small medical infrastructure in Limousin so that fewer ill-people choose to live in this place. Conversely, ill-people may choose the Riviera for its better climate.

The basic determinants of women's health remain valid for men (Table 3). The probability to get a health problem strongly increases with age (+20 points over 46 years old) and also diminishes with the education level. When the parents got a serious health problem during, the child has a stronger probability to have a health problem (+ 7 points). Contrary to women, however, men that have not been breaded by their parents or that have been separated from their family suffer no additional health problem. The residential effects can also differ: compared to the Paris area, men have more often health problems in Lorraine, and less often in Alsace, Centre, Languedoc-Roussillon and Limousin.

The determinants of the probability to be injured are reported in Table 6. As expected, being young increases the probability to have an accident for men but not for women. Compared to young women, the probability to have an accident is particularly significant for the elder women (46-55): the probability to be injured increases by 7 points over 46 years old. On the contrary, the education level is negatively correlated with the probability to have an accident for women: the higher the education level the lower the probability to be injured. This fact is stronger for men: it is for the most educated that the probability decreases.

The impact of the family matters for both women and men: the fact to have known her (his) father compared to people for whom the father was unknown has a negative impact on the probability to be injured. It is an important result. We may suppose that missing her or his father is related to the propensity to adopt a risky behavior or to be more vulnerable to injuries.

The living area also matters: living in disadvantaged urban areas (so-called "ZUS") is negatively correlated with the probability to have an accident for women only; this result could reflect the fact that the women living in "ZUS" would less often have a car license or drive a car. There are also regional residential effects: compared to Paris area, the probability to be injured notably increases for women in Midi Pyrénées and in Rhône Alpes. For men, we notice a lower probability to be injured in Region Centre. These results should be confronted with car injuries geography.

Regression and propensity score estimates

The next step of our econometric study is to compare the standard regression estimators ("naive regression estimators") with the estimators based on the propensity score. For this, we need to select the right control variables: we keep the variables that have a significant effect on the probability to have a health problem. We call the regression estimators "naive" because they do not explicitly account for the selection biases. Three estimators are reported : the comparison of the means, the OLS regression with a health problem dummy and the OLS regression with the health problem dummy and the cross products of the exogenous variables with the health problem dummy. For space reasons, we only report the coefficient of the health problem dummy in the Tables 4 and 5. All the standard errors are corrected for heteroskedasticity of unknown form. We report all the results in the Tables, but we comment on the most general model only, with the cross products.

Table 4 presents all the estimators concerning health problems for women. We start with the "naïve" estimators, and finish with the evaluation estimators in order to detect the potential biases from the regressions. We find that the women that had a health problem have more often experienced a long run unemployment period (+6 points). There are also less likely to have been working last week (-5%) and, when they worked, worked on a shorter period (- 2hrs/week). Their professional career is made of long unemployment periods followed by short employment periods (less than 1 year). Whatever the measure used, the women with health problems earn less than the other women and have a much lower subjective satisfaction degree about their professional career. They have a higher probability to earn less than 1200 Euros and a lower probability to earn more than 4000 Euros.

The comparison with the naive estimators concerning injuries for women reveals similar effects, with some differences (Table 7). There is no significant impact on revenues and on the number of hours worked during the previous week. We notice however stronger effects on the existence of short employment periods. Moreover women having experienced injuries have a lower probability to earn more than 1500 euros.

Consider now the evaluation estimators (Table 9): we find that the regression and propensity score estimators provide similar results for most variables for both health problems and injuries. The only difference is that, with the evaluation estimators, sick women have been working less often during the previous month, while it does not appear with the regression estimators. For injured women we find that, according to the evaluation estimators, the percentage of long employment periods and the experience of work the week preceding the interview are not affected significantly with injuries.

This similarity of the results between the two methods could come from two properties of our estimators: first, we have chosen the control variables from the Probit regression used to compute the propensity score; second, the common support of the propensity scores distributions of the treated and the not treated represents 95% of the data for most estimators so that there is almost no sampling variation between the naive and the evaluation estimators.

Table 5 presents all the estimators concerning health problems for men. The results are close to the one for women, except that health problems seem to favor both inactivity (+6%) and long run unemployment (+6%) and that the wage loss is higher for that part of the men that work (200 Euros/month instead of 100 Euros for women). Health problems weaken the whole employment career, and this is clearly related to the subjective satisfaction degree, which is much smaller for the people with health problems (-0.58). The estimations for men also present more differences between the methods : three effects are significant with the propensity score method while they were not with the cross products regression. First, sick men have less chances to have been working during the previous month (6 points), they have less chances to belong to the high-wage class, and they have more chances to get the minimum compensation revenue (i.e, a revenue given to any person without financial resources). There seems to be more selection effect among men than among women.

Table 8 presents the naïve estimators concerning injuries for men. The results also reveal similarities and some differences with the results concerning health problems. Regarding the differences, we particularly find that the injured men contrary to sick men and similarly with women do not significantly experience inactivity periods. The other differences concern the perception of minimum compensation income (RMI) and the subjective satisfaction degree of the professional career. The probability to get the minimum compensation income is not affected. It is the same with the subjective degree of satisfaction concerning the professional career. These differences also appear when we compare these results with those of women. Indeed, for injured women, perception of the minimum compensation income (that is the probability to become poor) is significantly increased, and subjective satisfaction on work as for sick women is significantly decreased.

Concerning the similarities with the results related to health problems, we also notice that injured men have more chances to belong to the low-wage class and to face long run unemployment periods.

Evaluation estimators (Table 10) concerning injured men reveal a rather different picture: the accidents significantly increases the number of inactivity and unemployment periods. Conversely, the impact on long run unemployment periods and on percentage of long run employment periods disappear.

4. Conclusion

In this first draft we look at whether and how the chronic and significant diseases influence the professional career. We find that, for both women and men, a significant health problem affects all the dimensions of it. For women, health problem impeaches to reach a stable employment status. For the women that work, there is a significant loss of revenues, and a global dissatisfaction about the employment career.

We reach a similar conclusion for men but with three differences. First, having significant health problems increases the chances to be inactive instead of unemployed. Second, the revenues are strongly affected by health problems, but twice as much as for women, which can be explained by the fact that men work mostly full time, and the women part time. Third, health problems increase the probability to depend on the minimum compensation revenue (the lowest achievable in France), which is associated to inactivity. This also leads to a global dissatisfaction about the employment career.

The next step of this study, it to look at how these effects compare with the performances variations associated with random (domestic and car) injuries.

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Table 1 – Sample Statistics: Differences according to the existence of health problems

	Without health problems (1)		With health problems (2)		Difference (2)-(1)	Student
	Obs	Mean	Obs	Mean		
General information :						
Age (19-55 years)	4804	38,07	1110	42,48	**4,41**	**13,65**
Women	4804	56,8%	1110	59,5%	*2,7%*	*1,65*
Presence of children	4804	68,6%	1110	77,0%	**8,5%**	**5,92**
Number of children	3294	2,17	855	2,33	**0,16**	**3,51**
Lives in underprivileged suburbs	4804	6,7%	1110	7,1%	0,4%	0,49
Highest education degree :						
Missing	4804	13,0%	1110	14,5%	1,5%	1,32
Primary education	4804	2,8%	1110	7,6%	**4,7%**	**5,71**
Secondary education (professional training)	4804	29,1%	1110	33,8%	**4,7%**	**2,99**
Secondary education (general)	4804	5,4%	1110	5,9%	0,4%	0,54
Professionnal baccalauréat (O-level, general)	4804	10,0%	1110	8,5%	-1,5%	1,64
General baccalauréat (O-level, professional)	4804	7,6%	1110	8,0%	0,4%	0,42
Two years of college education	4804	13,6%	1110	9,0%	**-4,6%**	**4,60**
At least three year of college education	4804	18,4%	1110	12,8%	**-5,7%**	**4,92**
Occupational status :						
Missing	4804	22,6%	1110	29,5%	**6,9%**	**4,62**
State worker	4804	12,3%	1110	11,2%	-1,2%	1,11
Local administration worker (+public housing, hospitals)	4804	7,5%	1110	8,0%	0,5%	0,58
Private sector (salaried, craftman, associations)	4804	47,4%	1110	43,4%	**-4,0%**	**2,42**
Salaried by a private individual	4804	2,2%	1110	2,5%	0,3%	0,57
No-wage family support	4804	0,6%	1110	0,7%	0,2%	0,58
Owner, CEO, Manager	4804	1,1%	1110	0,5%	**-0,6%**	**2,25**
Independent worker	4804	6,2%	1110	4,1%	**-2,1%**	**3,10**
Professional career :						
Existence of long-run unemployment periods	4804	16,2%	1110	23,8%	**7,6%**	**5,47**
% of Long run unemployment periods / total career	779	16,28	264	15,31	-0,98	0,85
Existence of inactivity periods	4804	30,4%	1110	41,3%	**10,9%**	**6,72**
% of inactivity periods / total career	1459	29,53	458	32,05	2,53	1,62
Recent activity :						
Had been working last week	4804	76,5%	1110	69,0%	**-7,5%**	**4,95**
Number of hours worked last week	3676	38,53	766	36,87	**-1,66**	**3,57**
Had a wage last month	4804	77,6%	1110	70,2%	**-7,4%**	**4,92**
Wage of the previous month (Euros)	3726	1777,16	779	1576,07	**-201,09**	**4,06**
Earnings' components of the household:						
Presence of non-wage incomes	4804	13,9%	1110	9,9%	**-4,0%**	**3,85**
Presence of retirement pension	4804	5,2%	1110	7,0%	**1,8%**	**2,22**
Presence of savings revenues	4804	35,6%	1110	35,5%	-0,1%	0,09
Average earnings :						
Missing average revenue	4804	4,3%	1110	3,2%	*-1,1%*	*1,89*
Less than 1200 Euros	4804	13,3%	1110	20,5%	**7,1%**	**5,46**
1200-2500 Euros	4804	39,4%	1110	40,1%	0,7%	0,41
2500-4000 Euros	4804	29,5%	1110	27,0%	*-2,5%*	*1,67*
More than 4000 Euros	4804	13,4%	1110	9,3%	**-4,2%**	**4,16**

Table 2 – Women: Probability to have a health problem

	Basic model			Backward elimination (10%)			
	Coefficient	Std error	Student	Coefficient	Std error	Student	Average absolute effect on probability
Intercept	-1.051	0.194	5.43	-0.971	0.141	6.88	
Age class :							
19-27	Ref						
28-36	0.273	0.094	2.92	0.232	0.090	2.59	**+6.3%**
37-45	0.372	0.090	4.14	0.320	0.085	3.75	**+8.7%**
46-55	0.618	0.087	7.08	0.568	0.082	6.89	**+16.1%**
Highest education achieved :							
Missing	Ref						
Primary education	0.288	0.138	2.09	0.413	0.121	3.42	**+12.4%**
Secondary education (professional training)	-0.243	0.130	1.88				
Secondary education (general)	-0.168	0.090	1.88				
Professionnal baccalauréat (O-level, general)	-0.293	0.116	2.53	-0.167	0.095	1.75	**-4.1%**
General baccalauréat (O-level, professional)	-0.120	0.111	1.08				
Two years of college education	-0.322	0.106	3.05	-0.193	0.082	2.34	**-4.7%**
At least three year of college education	-0.259	0.097	2.67	-0.139	0.070	1.97	**-3.5%**
Lives in underprivileged suburbs	-0.022	0.102	0.22				
Childhood :							
Foreign mother	0.059	0.125	0.47				
Foreign father	0.028	0.119	0.23				
Breeded by the father	0.076	0.093	0.82				
Breeded by the mother	-0.373	0.130	2.88	-0.326	0.119	2.73	**-9.5%**
Born in France	0.073	0.111	0.65				
Parents had serious health problems	0.317	0.069	4.60	0.308	0.068	4.52	**+8.8%**
Separated from family	0.195	0.084	2.33	0.169	0.079	2.15	**+4.6%**
Location :							
Alsace	-0.051	0.152	0.34				
Aquitaine	0.212	0.126	1.68				
Auvergne	-0.077	0.214	0.36				
Basse-Normandie	0.203	0.176	1.15				
Bourgogne	0.040	0.162	0.25				
Bretagne	0.178	0.130	1.37				
Centre	0.010	0.148	0.07				
Champagne-Ardenne	0.115	0.161	0.71				
Corse	0.380	0.510	0.75				
Franche-Comté	0.344	0.176	1.96	0.274	0.167	1.64	**+7.9%**
Haute-Normandie	0.087	0.167	0.52				
Île-de-France (Paris area)	réf						
Languedoc-Roussillon	0.243	0.141	1.73				
Limousin	-0.619	0.368	1.68	-0.672	0.361	1.86	**-12.8%**
Lorraine	0.397	0.135	2.94	0.329	0.123	2.67	**+9.6%**
Midi-Pyrénées	0.441	0.139	3.17	0.386	0.128	3.01	**+11.5%**
Nord-Pas-de-Calais	0.188	0.114	1.65				
Pays de la Loire	0.052	0.120	0.43				
Picardie	-0.004	0.149	0.03				
Poitou-Charentes	0.029	0.165	0.18				
Provence-Alpes-Côte d'Azur (Riviera)	0.275	0.104	2.65	0.219	0.089	2.45	**+6.1%**
Rhône-Alpes	-0.091	0.113	0.80				
% concordant predictions	66.0			63.2			
Mac Fadden pseudo R2	0.058			0.053			

Table 3 - Men: Probability to have a health problem

	Basic model			Backward elimination (10%)			
	Coefficient	Std error	Student	Coefficient	Std error	Student	Average absolute effect on probability
Intercept	-1.380	0.243	5.69	-1.274	0.087	14.73	
Age class :							
19-27	réf						
28-36	0.315	0.111	2.84	0.298	0.108	2.77	**+7.8%**
37-45	0.402	0.106	3.80	0.372	0.101	3.68	**+9.6%**
46-55	0.774	0.103	7.52	0.731	0.098	7.46	**+20.1%**
Highest education achieved :							
Missing	réf						
Primary education	0.208	0.167	1.25	0.234	0.143	1.64	**+6.3%**
Secondary education (professional training)	-0.104	0.154	0.67				
Secondary education (general)	-0.033	0.105	0.31				
Professionnal baccalauréat (O-level, general)	-0.033	0.130	0.25				
General baccalauréat (O-level, professional)	-0.259	0.160	1.62	-0.237	0.134	1.77	**-5.3%**
Two years of college education	-0.354	0.133	2.66	-0.313	0.103	3.03	**-6.9%**
At least three year of college education	-0.398	0.128	3.11	-0.370	0.095	3.88	**-8.0%**
Lives in underprivileged suburbs	0.051	0.132	0.39				
Childhood :							
Foreign mother	-0.057	0.142	0.40				
Foreign father	0.109	0.142	0.77				
Breeded by the father	-0.106	0.113	0.94				
Breeded by the mother	0.029	0.171	0.17				
Born in France	0.188	0.129	1.45				
Parents had health problems	0.244	0.090	2.72	0.256	0.088	2.90	**+6.8%**
Separated from familly	0.064	0.103	0.62				
Location :							
Alsace	-0.437	0.228	1.92	-0.434	0.217	2.01	**-8.7%**
Aquitaine	-0.131	0.154	0.85				
Auvergne	0.104	0.222	0.47				
Basse-Normandie	0.117	0.220	0.53				
Bourgogne	-0.156	0.210	0.74				
Bretagne	-0.190	0.157	1.21				
Centre	-0.340	0.184	1.84	-0.334	0.171	1.96	**-7.1%**
Champagne-Ardenne	-0.006	0.197	0.03				
Corse	-0.555	0.567	0.98				
Franche-Comté	-0.304	0.226	1.34				
Haute-Normandie	-0.211	0.227	0.93				
Île-de-France (Paris area)	réf						
Languedoc-Roussillon	-0.393	0.201	1.96	-0.389	0.188	2.06	**-8.0%**
Limousin	-0.592	0.315	1.88	-0.587	0.305	1.92	**-10.9%**
Lorraine	0.302	0.154	1.96	0.316	0.138	2.29	**+8.7%**
Midi-Pyrénées	0.175	0.164	1.06				
Nord-Pas-de-Calais	-0.032	0.135	0.24				
Pays de la Loire	0.139	0.136	1.02				
Picardie	0.050	0.167	0.30				
Poitou-Charentes	0.095	0.192	0.49				
Provence-Alpes-Côte d'Azur (Riviera)	0.011	0.136	0.08				
Rhône-Alpes	0.036	0.121	0.29				
% of concordant predictions	68.2			63.7			
Mac Fadden pseudo R2	0.068			0.061			

Table 4 - Women: causal effect of health problems (naive and evaluation estimators)

The standard errors of the naive estimators are robust to heterosckedasticity. The standard errors of the evaluation estimators account for the first-stage estimation of the Probit model .

	Statistics	NAIVE ESTIMATORS Sample size	NAIVE ESTIMATORS Difference of the means	NAIVE ESTIMATORS OLS with health dummy	NAIVE ESTIMATORS OLS with cross products	EVALUATION ESTIMATORS Common support (% sample size)	EVALUATION ESTIMATORS Average treatment effect	EVALUATION ESTIMATORS Effect on the not treated	EVALUATION ESTIMATORS Effect on the treated
Existence of long-run unemployment periods (> 1 year)	Effect	3392	**0.074**	**0.049**	**0.053**	3253 (95.9%)	**0,055**	**0,055**	**0,056**
	p-value		0.000	0.009	0.004		0,003	0,004	0,005
% of Long run unemployment periods / total career	Effect	695	-1.334	0.755	-0.726	635 (91.4%)	0,471	0,343	0,831
	p-value		0.325	0.546	0.540		0,701	0,787	0,530
Existence of inactivity periods	Effect	3392	**0.117**	**0.042**	0.029	3253 (95.9%)	0,023	0,020	0,034
	p-value		0.000	0.039	0.142		0,268	0,333	0,115
% of inactivity periods / total career	Effect	1200	0.603	-0.258	-1.088	1112 (92.7%)	-2,245	-2,195	-2,401
	p-value		0.764	0.899	0.602		0,331	0,371	0,280
Existence of long employment periods (>1 yearr	Effect	3392	**0.060**	-0.005	-0.005	3253 (95.9%)	-0,006	-0,004	-0,013
	p-value		0.002	0.780	0.779		0,766	0,836	0,471
% of long employment periods / total career	Effect	2299	**-6.536**	**-4.436**	**-4.322**	2101 (91.4%)	**-3,453**	*-3,223*	**-4,319**
	p-value		0.000	0.001	0.001		0,044	0,082	0,003
Existence of short employment periods (<=1 year)	Effect	3392	**0.053**	**0.043**	**0.060**	3253 (95.9%)	**0,061**	**0,066**	*0,037*
	p-value		0.008	0.034	0.004		0,013	0,011	0,088
% of short employment periods / total career	Effect	2236	**-6.395**	0.594	0.418	2183 (97.6%)	1,790	2,141	0,422
	p-value		0.000	0.622	0.755		0,385	0,353	0,748
Had been working last week	Effect	3392	**-0.071**	**-0.069**	**-0.050**	3253 (95.9%)	**-0,052**	*-0,045*	**-0,081**
	p-value		0.001	0.001	0.015		0,034	0,082	0,000
Number of hours worked last week	Effect	2371	**-1.929**	**-1.770**	**-1.557**	2290 (96.6%)	*-1,459*	-1,394	**-1,756**
	p-value		0.001	0.003	0.011		0,079	0,115	0,008
Existence of long-run unemployment periods (v2)	Effect	3392	**0.073**	**0.049**	**0.052**	3253 (95.9%)	**0,054**	**0,054**	**0,055**
	p-value		0.000	0.010	0.005		0,004	0,005	0,006
Number of long run employment periods	Effect	708	0.075	0.038	0.030	653 (92.2%)	0,033	0,034	0,028
	p-value		0.112	0.406	0.470		0,523	0,539	0,585
Existence of short employment periods (v2)	Effect	3392	**0.049**	**0.047**	**0.064**	3253 (95.9%)	**0,064**	**0,069**	*0,040*
	p-value		0.011	0.017	0.001		0,009	0,007	0,055
Number of short employment periods	Effect	2360	0.029	-0.029	-0.032	2254 (95.5%)	-0,045	-0,043	-0,051
	p-value		0.461	0.460	0.385		0,283	0,316	0,237

(to be followed)

(followed from Table 4)	Statistics	Sample size	Difference of the means	OLS with health dummy	OLS with cross products	Common support (% sample size)	Average treatment effect	Effect on the not treated	Effect on the treated
Existence of long run employment periods (v2)	Effect	3392	**0.058**	-0.007	-0.007	3253 (95.9%)	-0,008	-0,007	-0,015
	p-value		0.003	0.676	0.685		0,681	0,754	0,395
Number of long run employment periods	Effect	2305	0.044	-0.029	-0.039	2132 (92.5%)	-0,039	-0,038	-0,046
	p-value		0.145	0.329	0.138		0,197	0,226	0,153
Existence of inactivity periods	Effect	3392	**0.117**	**0.043**	0.032	3253 (95.9%)	0,026	0,024	0,035
	p-value		0.000	0.036	0.115		0,214	0,259	0,112
Number of inactivity periods	Effect	1209	0.017	-0.006	-0.013	1159 (95.8%)	0,007	0,018	-0,027
	p-value		0.625	0.855	0.710		0,888	0,762	0,496
Existence of a revenue last month	Effect	3392	**-0.067**	**-0.056**	-0.032	3253 (95.9%)	-0,035	-0,026	**-0,074**
	p-value		0.001	0.005	0.117		0,159	0,324	0,001
Last month revenue (Euros)	Effect	2406	**-122.07**	**-113.69**	**-99.00**	2317 (96.3%)	-84,28	-75,85	**-123,13**
	p-value		0.033	0.050	0.090		0,193	0,256	0,042
Last month revenue is representative	Effect	3392	**-0.070**	**-0.062**	**-0.045**	3253 (95.9%)	-0,034	-0,027	**-0,065**
	p-value		0.001	0.004	0.041		0,174	0,304	0,005
The household benefits from RMI	Effect	3392	**0.026**	*0.018*	*0.017*	3253 (95.9%)	*0,016*	*0,016*	0,014
	p-value		0.008	0.065	0.068		0,097	0,092	0,156
Subjective satisfaction degree of the professional career	Effect	3174	**-0.665**	**-0.586**	**-0.582**	3036 (95.6%)	**-0,605**	**-0,573**	**-0,738**
	p-value		0.000	0.000	0.000		0,000	0,002	0,000
Missing revenue	Effect	3392	-0.004	-0.003	0.000	3253 (95.9%)	0,000	0,001	-0,004
	p-value		0.628	0.735	0.993		0,996	0,928	0,659
Less than 1200 Euros	Effect	3392	**0.068**	**0.063**	**0.057**	3253 (95.9%)	**0,046**	**0,043**	**0,056**
	p-value		0.000	0.000	0.001		0,010	0,017	0,002
1200 -1500 Euros	Effect	3392	-0.009	-0.011	-0.009	3253 (95.9%)	-0,020	-0,019	-0,026
	p-value		0.686	0.621	0.693		0,390	0,440	0,249
1500-4000 Euros	Effect	3392	-0.022	-0.016	-0.018	3253 (95.9%)	-0,002	-0,001	-0,008
	p-value		0.240	0.419	0.360		0,922	0,972	0,703
More than 4000 Euros	Effect	3392	**-0.033**	**-0.034**	**-0.030**	3253 (95.9%)	**-0,031**	**-0,030**	**-0,035**
	p-value		0.011	0.008	0.023		0,028	0,040	0,008

Table 5 - Men: causal effect of health problems (naive and evaluation estimators)

The standard errors of the naive estimators are robust to heterosckedasticity. The standard errors of the evaluation estimators account for the first-stage estimation of the Probit model .

			NAIVE ESTIMATORS			EVALUATION ESTIMATORS			
	Statistics	**Sample size**	**Difference of the means**	**OLS with health dummy**	**OLS with cross products**	**Common support (% sample size)**	**Average treatment effect**	**Effect on the not treated**	**Effect on the treated**
Existence of long-run unemployment periods (> 1 year)	Effect	2522	**0.073**	**0.058**	*0.034*	2381 (94.4%)	**0,041**	*0,036*	**0,065**
	p-value		0.000	0.004	0.069		0,032	0,063	0,003
% of Long run unemployment periods / total career	Effect	348	-0.267	*3.734*	*4.358*	301 (86.5%)	4,280	4,440	*3,880*
	p-value		0.901	0.068	0.076		0,166	0,230	0,070
Existence of inactivity periods	Effect	2522	**0.093**	**0.066**	**0.062**	2381 (94.4%)	**0,072**	**0,073**	**0,070**
	p-value		0.000	0.008	0.013		0,010	0,014	0,008
% of inactivity periods / total career	Effect	717	**3.838**	**5.236**	**4.260**	676 (94.3%)	**4,728**	**4,347**	**5,964**
	p-value		0.012	0.000	0.006		0,001	0,003	0,000
Existence of long employment periods (>1 yearr)	Effect	2522	**0.069**	**-0.043**	-0.032	2381 (94.4%)	-0,029	-0,026	-0,040
	p-value		0.001	0.011	0.108		0,301	0,391	0,026
% of long employment periods / total career	Effect	1907	-2.008	**-2.969**	*-2.189*	1801 (94.4%)	-2,312	-2,065	**-3,384**
	p-value		0.113	0.018	0.094		0,344	0,452	0,022
Existence of short employment periods (<=1 year)	Effect	2522	0.039	0.039	0.035	2381 (94.4%)	0,027	0,025	0,035
	p-value		0.102	0.111	0.185		0,366	0,428	0,173
% of short employment periods / total career	Effect	1694	**-8.711**	1.391	0.552	1616 (95.4%)	0,213	-0,022	1,219
	p-value		0.000	0.369	0.755		0,936	0,994	0,462
Had been working last week	Effect	2522	**-0.072**	**-0.096**	**-0.065**	2381 (94.4%)	**-0,067**	*-0,059*	**-0,100**
	p-value		0.001	0.000	0.005		0,027	0,071	0,000
Number of hours worked last week	Effect	2071	-1.017	-1.031	-0.894	1998 (96.5%)	-1,120	-1,120	-1,117
	p-value		0.127	0.128	0.210		0,336	0,379	0,145
Existence of long-run unemployment periods (v2)	Effect	2522	**0.076**	**0.060**	*0.037*	2381 (94.4%)	**0,044**	**0,038**	**0,067**
	p-value		0.000	0.003	0.053		0,025	0,049	0,002
Number of long run employment periods	Effect	354	0.040	0.026	0.027	300 (84.7%)	0,034	0,038	0,024
	p-value		0.550	0.708	0.688		0,754	0,765	0,765
Existence of short employment periods (v2)	Effect	2522	**0.039**	**0.048**	*0.047*	2381 (94.4%)	0,037	0,036	0,041
	p-value		0.093	0.044	0.061		0,205	0,245	0,102
Number of short employment periods	Effect	1773	-0.022	-0.040	-0.054	1713 (96.6%)	-0,078	-0,085	-0,044
	p-value		0.623	0.393	0.226		0,165	0,151	0,375

(to be followed)

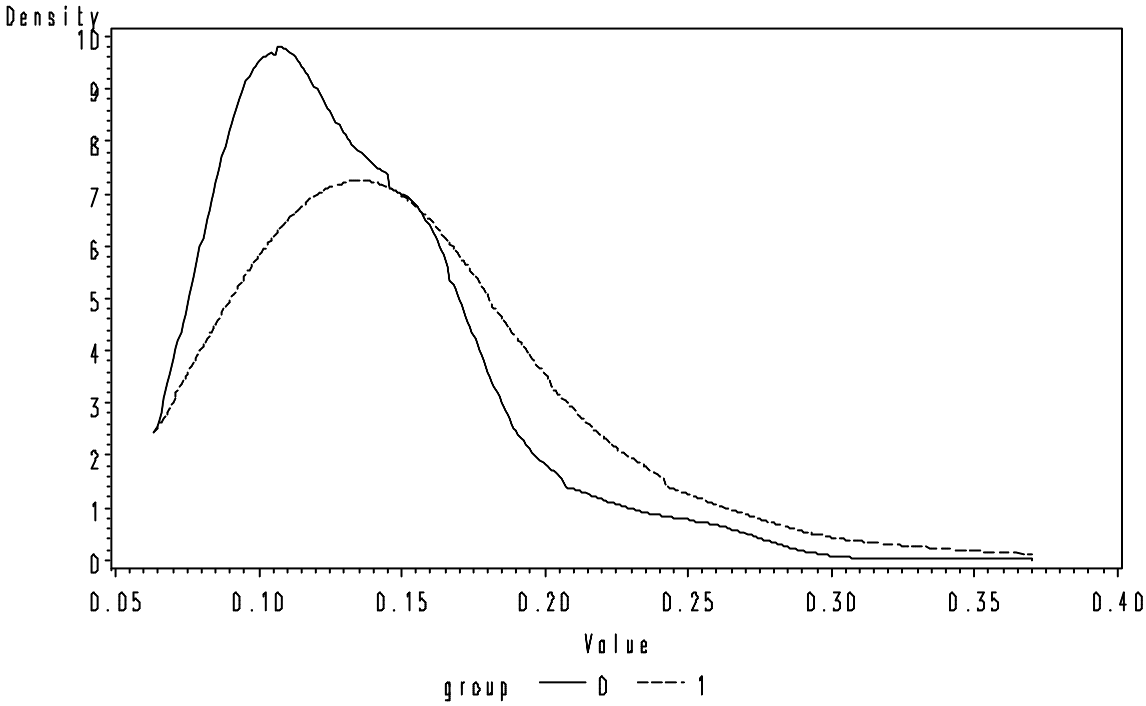
(followed from Table 5)	Statistics	Sample size	Difference of the means	OLS with health dummy	OLS with cross products	Common support (% sample size)	Average treatment effect	Effect on the not treated	Effect on the treated
Existence of long run employment periods (v2)	Effect	2522	**0.070**	**-0.042**	-0.032	2381 (94.4%)	-0,029	-0,026	**-0,039**
	p-value		0.001	0.012	0.107		0,300	0,385	0,030
Number of long run employment periods	Effect	1911	**0.083**	0.007	-0.005	1851 (96.9%)	0,001	-0,003	0,018
	p-value		0.029	0.855	0.892		0,977	0,959	0,662
Existence of inactivity periods	Effect	2522	**0.101**	**0.073**	**0.067**	2381 (94.4%)	**0,078**	**0,077**	**0,078**
	p-value		0.000	0.003	0.007		0,006	0,009	0,003
Number of inactivity periods	Effect	724	**0.099**	**0.073**	*0.057*	669 (92.4%)	0,076	0,072	**0,088**
	p-value		0.004	0.028	0.059		0,101	0,165	0,020
Existence of a revenue last month	Effect	2522	**-0.075**	**-0.073**	*-0.040*	2381 (94.4%)	*-0,052*	-0,046	**-0,078**
	p-value		0.000	0.001	0.058		0,082	0,153	0,001
Last month revenue (Euros)	Effect	2099	**-267.06**	**-293.05**	**-220.65**	2012 (95.8%)	**-232,12**	**-231,13**	**-237,24**
	p-value		0.001	0.006	0.012		0,009	0,011	0,007
Last month revenue is representative	Effect	2522	-0.037	**-0.054**	-0.025	2381 (94.4%)	-0,030	-0,024	**-0,057**
	p-value		0.131	0.028	0.331		0,346	0,480	0,030
The household benefits from RMI (min. comp. revenue)	Effect	2522	**0.024**	**0.021**	0.013	2381 (94.4%)	*0,016*	*0,013*	**0,026**
	p-value		0.014	0.028	0.104		0,054	0,086	0,014
Subjective satisfaction degree of the professional career	Effect	2439	**-0.734**	**-0.759**	**-0.720**	2301 (94.3%)	**-0,821**	**-0,821**	**-0,823**
	p-value		0.000	0.000	0.000		0,000	0,000	0,000
Missing revenue	Effect	2522	**-0.022**	**-0.020**	*-0.017*	2381 (94.4%)	*-0,017*	-0,016	**-0,021**
	p-value		0.003	0.012	0.065		0,077	0,112	0,013
Less than 1200 Euros	Effect	2522	**0.073**	**0.081**	**0.060**	2381 (94.4%)	**0,063**	**0,059**	**0,084**
	p-value		0.000	0.000	0.004		0,003	0,008	0,000
1200 -1500 Euros	Effect	2522	0.029	0.013	0.008	2381 (94.4%)	-0,002	-0,004	0,006
	p-value		0.262	0.620	0.768		0,938	0,893	0,829
1500-4000 Euros	Effect	2522	-0.027	-0.033	-0.028	2381 (94.4%)	-0,022	-0,021	-0,029
	p-value		0.261	0.176	0.264		0,430	0,486	0,246
More than 4000 Euros	Effect	2522	**-0.053**	**-0.041**	-0.023	2381 (94.4%)	-0,025	-0,022	**-0,039**
	p-value		0.001	0.009	0.230		0,198	0,295	0,010

Table 6 : Probit regressions, probability to be injured

	women p=13,4%		Backward selection		Average effects	**men p=23,3%**		Backward selection		Average effect
	Coeff	Student	Coeff	Student		Coeff	Student	Coeff	Student	
Intercept	-0,927	4,45	-1,091	13,11		-1,196	5,72	-1,000	8,06	
Age class :										
19-27	Réf					Réf				
28-36	0,020	0,20				0,251	2,81	0,281	3,26	0,088
37-45	0,137	1,49	0,114	1,63	0,025	0,269	3,12	0,286	3,50	0,089
46-55	0,317	3,55	0,300	4,53	0,068	0,389	4,47	0,410	5,00	0,130
Highest education achieved:										
Missing	Réf					Réf				
Primary education	-0,180	1,00				0,100	0,59			
General secondary educ.	0,137	1,07	0,354	3,44	0,088	0,172	1,27			
Secondary education (professional training)	-0,218	2,22				0,088	0,92			
Professional baccalaureat	-0,296	2,35				0,166	1,45			
General baccalaureat	-0,221	1,78				0,084	0,62			
Two years of college education	-0,285	2,52				-0,098	0,85	-0,201	2,34	-0,057
At least three years of college education	-0,244	2,33				-0,156	1,39	-0,270	3,42	-0,075
Living in underprivileged suburbs	-0,213	1,68	-0,217	1,77	-0,041	0,069	0,59			
Foreign mother	0,054	0,39				-0,071	0,55			
Foreign father	-0,168	1,23				0,007	0,06			
Breeded by the father	-0,176	1,92	-0,218	2,66	-0,050	-0,186	2,04	-0,154	1,88	-0,048
Breeded by the mother	-0,079	0,51				0,158	1,03			
Born in France	-0,067	0,55				0,161	1,37	0,228	2,63	0,064
Regional location :										
Alsace	0,115	0,70				0,198	1,23			
Aquitaine	0,313	2,30				0,076	0,59			
Auvergne	0,139	0,63				0,180	0,90			
Basse-Normandie	0,205	1,05				0,273	1,49			
Bourgogne	0,339	2,05				0,202	1,19			
Bretagne	0,207	1,44				0,064	0,49			
Centre	0,233	1,50				-0,239	1,54	-0,297	2,09	-0,080
Champagne-Ardenne	-0,032	0,16				0,145	0,84			
Corse	0,061	0,10				-0,101	0,23			
Franche-Comté	0,246	1,22				-0,199	1,00			
Haute-Normandie	-0,038	0,18				0,096	0,53			
Île-de-France	Réf					Réf				
Languedoc-Roussillon	0,157	0,96				-0,062	0,40			
Limousin	0,267	1,06				0,060	0,29			
Lorraine	0,178	1,09				0,144	0,97			
Midi-Pyrénées	0,454	2,92	0,323	2,28	0,080	0,133	0,90			
Nord-Pas-de-Calais	-0,012	0,09				0,030	0,25			
Pays de la Loire	0,180	1,37				0,112	0,90			
Picardie	0,116	0,71				-0,090	0,56			
Poitou-Charentes	0,284	1,66				0,027	0,15			
Provence-Alpes-Côte d'Azur	0,188	1,51				0,063	0,52			
Rhône-Alpes	0,319	2,83	0,176	1,88	0,040	0,034	0,31			
% concordant predictions	61,8%		52,6%			60,4%		55,3%		

Probability to be injured: Comparison of the treatment probability supports

WOMEN



MEN

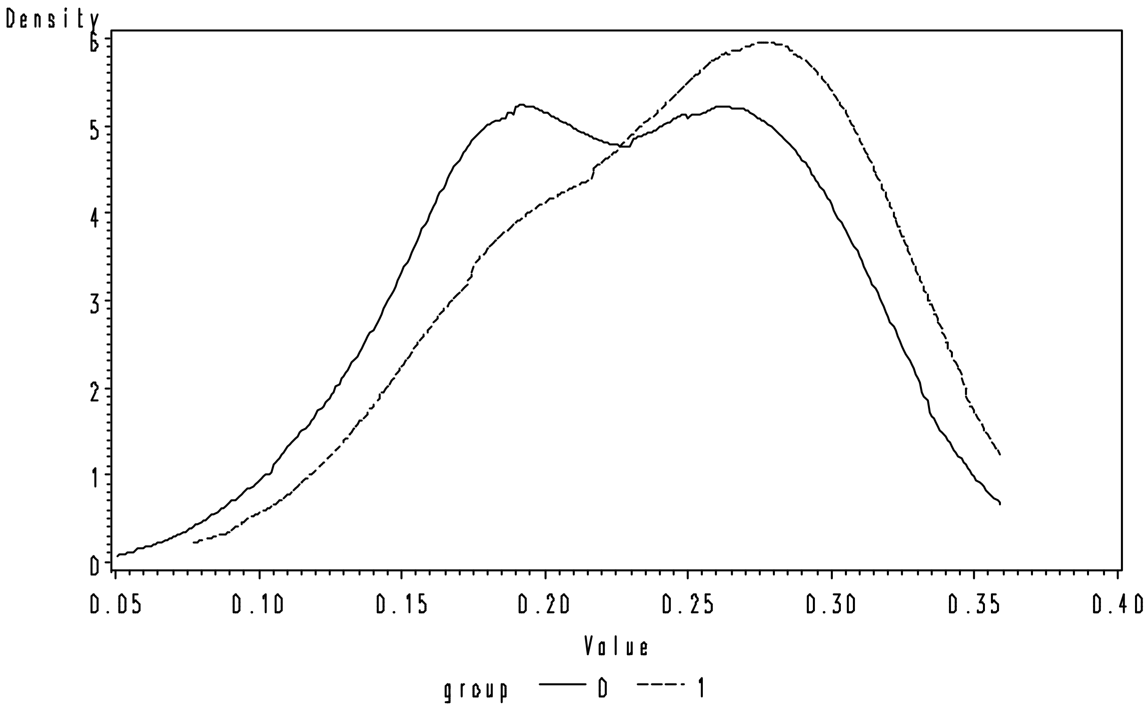


Table 7- Women: Effect of an accident, naïve estimators

Standard errors robust to heteroskedasticity

	Statistics	Difference of the means	OLS	OLS with cross products	Obs.
Existence of long run unemployment periods (> 1 year)	Effect	**0,061**	**0,053**	**0,050**	3251
	Standard error	0,022	0,022	0,022	
	p- value	0,005	0,017	0,021	
% of long run unemployment periods /total career	Effect	-0,768	1,772	1,810	646
	Standard error	1,689	1,487	1,810	
	p- value	0,649	0,234	0,317	
Existence of inactivity periods	Effect	**0,126**	**0,096**	**0,089**	3251
	Standard error	0,025	0,025	0,025	
	p- value	0,000	0,000	0,000	
% of inactivity periods /total career	Effect	-0,736	0,221	-1,061	1133
	Standard error	2,321	2,358	2,373	
	p- value	0,751	0,925	0,655	
Existence of long employment periods (> 1 year)	Effect	0,008	*-0,036*	-0,027	3251
	Standard error	0,024	0,022	0,023	
	p- value	0,739	0,095	0,242	
% of long employment periods /total career	Effect	**-5,864**	**-5,477**	**-5,395**	2172
	Standard error	1,565	1,570	1,574	
	p- value	0,000	0,000	0,001	
Existence of short employment periods (<= 1 year)	Effect	**0,092**	**0,091**	**0,097**	3251
	Standard error	0,023	0,023	0,023	
	p- value	0,000	0,000	0,000	
% of short employment periods /total career	Effect	*-3,446*	-0,656	-0,396	2151
	Standard error	1,864	1,560	1,683	
	p- value	0,065	0,674	0,814	
Had been working last year	Effect	*-0,040*	**-0,056**	*-0,041*	3251
	Standard error	0,024	0,024	0,025	
	p- value	0,092	0,021	0,095	
Number of hours worked last week	Effect	-0,682	-0,685	-0,757	2301
	Standard error	0,741	0,740	0,755	
	p- value	0,357	0,355	0,316	
Existence of long run unemployment periods	Effect	**0,060**	**0,051**	**0,049**	3251
	Standard error	0,022	0,022	0,022	
	p- value	0,007	0,021	0,026	
Number of long run employment periods	Effect	0,096	0,083	0,072	658
	Standard error	0,064	0,064	0,060	
	p- value	0,129	0,193	0,228	
Existence of short employment periods	Effect	**0,093**	**0,095**	**0,096**	3251
	Standard error	0,022	0,022	0,022	
	p- value	0,000	0,000	0,000	
Number of short employment periods	Effect	0,073	0,051	0,059	2275
	Standard error	0,052	0,052	0,054	
	p- value	0,159	0,327	0,272	
Existence of long employment periods	Effect	0,008	*-0,036*	-0,027	3251
	Standard error	0,024	0,022	0,023	
	p- value	0,733	0,096	0,240	

Standard errors robust to heteroskedasticity

(followed from table 7)	Statistics	Difference of the means	OLS	OLS with cross products	Obs.
Number of long run employment periods	Effect	0,023	-0,018	-0,011	2179
	Standard error	0,034	0,034	0,031	
	p- value	0,497	0,598	0,736	
Existence of inactivity periods	Effect	**0,126**	**0,096**	**0,089**	3251
	Standard error	0,025	0,025	0,025	
	p- value	0,000	0,000	0,000	
Number of inactivity periods	Effect	**0,115**	**0,114**	**0,101**	1141
	Standard error	0,043	0,044	0,044	
	p- value	0,008	0,009	0,021	
Existence of a revenue last month	Effect	-0,012	-0,021	-0,009	3251
	Standard error	0,023	0,023	0,024	
	p- value	0,603	0,376	0,721	
Last month revenue (Euros)	Effect	-52,484	-53,970	-57,568	2355
	Standard error	64,653	63,475	61,544	
	p- value	0,417	0,395	0,350	
Last month revenue is representative	Effect	-0,040	*-0,048*	-0,040	3251
	Standard error	0,025	0,025	0,026	
	p- value	0,115	0,059	0,133	
The household benefits from RMI	Effect	**0,029**	**0,030**	**0,026**	3251
	Standard error	0,012	0,012	0,012	
	p- value	0,014	0,012	0,027	
Subjective satisfaction degree of the professional career	Effect	**-0,505**	**-0,514**	**-0,491**	3043
	Standard error	0,136	0,136	0,141	
	p- value	0,000	0,000	0,001	
Missing revenue	Effect	*-0,016*	*-0,015*	**-0,018**	3251
	Standard error	0,009	0,009	0,009	
	p- value	0,075	0,095	0,040	
Less than 1200 euros	Effect	**0,068**	**0,075**	**0,076**	3251
	Standard error	0,021	0,021	0,022	
	p- value	0,001	0,000	0,000	
1200 to 1500	Effect	0,031	0,030	0,032	3251
	Standard error	0,025	0,025	0,026	
	p- value	0,219	0,235	0,226	
1500 to 4000	Effect	**-0,047**	**-0,050**	**-0,054**	3251
	Standard error	0,022	0,022	0,022	
	p- value	0,033	0,022	0,013	
More than 4000 euros	Effect	**-0,036**	**-0,040**	**-0,036**	3251
	Standard error	0,015	0,015	0,015	
	p- value	0,016	0,008	0,018	

Table 8- Men: effect of an accident: naïve estimators

Standard errors robust to heteroskedasticity

	Statistics	Difference of the means	OLS	OLS with cross products	Obs.
Existence of long run unemployment periods (> 1 year)	Effect	**0,043**	**0,034**	*0,028*	2797
	Standard error	0,016	0,016	0,016	
	p- value	0,009	0,033	0,071	
% of long run unemployment periods /total career	Effect	-1,167	1,582	2,548	385
	Standard error	1,871	1,662	2,015	
	p- value	0,533	0,341	0,206	
Existence of inactivity periods	Effect	0,032	0,006	0,008	2797
	Standard error	0,020	0,020	0,020	
	p- value	0,120	0,759	0,698	
% of inactivity periods /total career	Effect	1,783	2,381	2,089	767
	Standard error	1,439	1,282	1,295	
	p- value	0,215	0,063	0,107	
Existence of long employment periods (> 1 year)	Effect	**0,043**	-0,022	-0,023	2797
	Standard error	0,019	0,014	0,014	
	p- value	0,022	0,107	0,103	
% of long employment periods /total career	Effect	**-2,558**	**-2,640**	**-2,664**	2116
	Standard error	1,053	1,007	1,025	
	p- value	0,015	0,009	0,009	
Existence of short employment periods (<= 1 year)	Effect	*0,038*	*0,035*	**0,041**	2797
	Standard error	0,021	0,020	0,021	
	p- value	0,066	0,087	0,049	
% of short employment periods /total career	Effect	-2,295	1,845	1,953	1885
	Standard error	1,780	1,358	1,401	
	p- value	0,197	0,174	0,163	
Had been working last year	Effect	-0,024	**-0,046**	**-0,042**	2797
	Standard error	0,017	0,016	0,017	
	p- value	0,160	0,005	0,015	
Number of hours worked last week	Effect	0,338	0,202	0,284	2320
	Standard error	0,574	0,573	0,562	
	p- value	0,556	0,725	0,613	
Existence of long run unemployment periods	Effect	**0,041**	**0,032**	*0,026*	2797
	Standard error	0,016	0,016	0,016	
	p- value	0,012	0,046	0,094	
Number of long run employment periods	Effect	-0,036	-0,063	-0,053	389
	Standard error	0,053	0,057	0,052	
	p- value	0,498	0,266	0,306	
Existence of short employment periods	Effect	**0,040**	**0,040**	**0,045**	2797
	Standard error	0,020	0,020	0,020	
	p- value	0,048	0,042	0,023	
Number of short employment periods	Effect	0,040	0,015	0,004	1972
	Standard error	0,049	0,048	0,046	
	p- value	0,417	0,754	0,926	
Existence of long employment periods	Effect	**0,041**	*-0,023*	*-0,024*	2797
	Standard error	0,019	0,014	0,014	
	p- value	0,026	0,084	0,083	

Standard errors robust to heteroskedasticity

(followed from table 8)	Statistics	Difference of the means	OLS	OLS with cross products	Obs.
Number of long run employment periods	Effect	0,025	-0,005	-0,008	2119
	Standard error	0,031	0,030	0,029	
	p- value	0,426	0,857	0,784	
Existence of inactivity periods	Effect	0,030	0,004	0,006	2797
	Standard error	0,020	0,020	0,020	
	p- value	0,144	0,847	0,774	
Number of inactivity periods	Effect	*0,044*	*0,044*	*0,043*	771
	Standard error	0,026	0,025	0,026	
	p- value	0,085	0,081	0,094	
Existence of a revenue last month	Effect	-0,011	-0,018	-0,016	2797
	Standard error	0,017	0,016	0,017	
	p- value	0,504	0,264	0,353	
Last month revenue (Euros)	Effect	**-173,420**	*-152,304*	-121,343	2356
	Standard error	75,541	79,299	76,220	
	p- value	0,022	0,055	0,111	
Last month revenue is representative	Effect	-0,007	-0,021	-0,013	2797
	Standard error	0,021	0,020	0,021	
	p- value	0,734	0,294	0,525	
The household benefits from RMI	Effect	0,004	0,004	0,006	2797
	Standard error	0,006	0,006	0,007	
	p- value	0,496	0,487	0,363	
Subjective satisfaction degree of the professional career	Effect	-0,153	-0,161	-0,146	2704
	Standard error	0,104	0,103	0,107	
	p- value	0,141	0,119	0,173	
Missing revenue	Effect	-0,002	-0,001	-0,003	2797
	Standard error	0,009	0,009	0,009	
	p- value	0,854	0,939	0,771	
Less than 1200 euros	Effect	**0,038**	**0,043**	**0,041**	2797
	Standard error	0,016	0,015	0,016	
	p- value	0,016	0,006	0,010	
1200 to 1500	Effect	0,001	-0,008	-0,014	2797
	Standard error	0,022	0,022	0,022	
	p- value	0,966	0,722	0,513	
1500 to 4000	Effect	-0,012	-0,019	-0,015	2797
	Standard error	0,021	0,021	0,021	
	p- value	0,552	0,350	0,460	
More than 4000 euros	Effect	*-0,025*	-0,015	-0,009	2797
	Standard error	0,015	0,014	0,015	
	p- value	0,094	0,287	0,561	

Table 9 - women: effect of an accident, evaluation estimators

The standard errors of the evaluation estimators account for the first stage estimation of the Probit model.

	Statistics	Average treatment effect	Effect on the non treated	Effect on the treated	Obs.
Existence of long run unemployment periods (> 1 year)	Effect	**0,062**	**0,062**	**0,066**	3087
	Standard error	0,023	0,023	0,023	
	p- value	0,006	0,007	0,004	
% of long run unemployment periods /total career	Effect	3,032	3,190	2,321	587
	Standard error	1,930	2,059	1,496	
	p- value	0,116	0,121	0,121	
Existence of inactivity periods	Effect	**0,101**	**0,099**	**0,112**	3087
	Standard error	0,026	0,026	0,026	
	p- value	0,000	0,000	0,000	
% of inactivity periods /total career	Effect	-2,399	-2,761	-0,605	1060
	Standard error	2,493	2,521	2,575	
	p- value	0,336	0,273	0,814	
Existence of long employment periods (> 1 year)	Effect	-0,021	-0,019	-0,029	3087
	Standard error	0,024	0,025	0,022	
	p- value	0,394	0,434	0,198	
% of long employment periods /total career	Effect	-1,988	-1,908	-2,447	1684
	Standard error	1,956	2,035	1,782	
	p- value	0,310	0,348	0,170	
Existence of short employment periods (<= 1 year)	Effect	**0,114**	**0,116**	**0,104**	3087
	Standard error	0,025	0,026	0,025	
	p- value	0,000	0,000	0,000	
% of short employment periods /total career	Effect	-0,444	-0,531	0,041	2011
	Standard error	1,831	1,879	1,636	
	p- value	0,808	0,777	0,980	
Had been working last year	Effect	-0,032	-0,030	**-0,051**	3087
	Standard error	0,026	0,027	0,025	
	p- value	0,218	0,269	0,045	
Number of hours worked last week	Effect	0,446	0,508	0,064	1659
	Standard error	0,961	0,989	0,858	
	p- value	0,643	0,608	0,941	
Existence of long run unemployment periods	Effect	**0,060**	**0,060**	**0,065**	3087
	Standard error	0,023	0,023	0,023	
	p- value	0,008	0,009	0,005	
Number of long run employment periods	Effect	*0,122*	*0,125*	0,107	608
	Standard error	0,066	0,068	0,068	
	p- value	0,065	0,064	0,117	
Existence of short employment periods	Effect	**0,112**	**0,113**	**0,106**	3087
	Standard error	0,024	0,025	0,024	
	p- value	0,000	0,000	0,000	
Number of short employment periods	Effect	0,078	0,075	*0,093*	2127
	Standard error	0,058	0,059	0,054	
	p- value	0,179	0,204	0,085	
Existence of long employment periods	Effect	-0,020	-0,019	-0,028	3087
	Standard error	0,024	0,025	0,022	
	p- value	0,398	0,436	0,204	

The standard errors of the evaluation estimators account for the first stage estimation of the Probit model.

(followed from table 10)	Statistics	Average treatment effect	Effect on the non treated	Effect on the treated	Obs.
Number of long run employment periods	Effect	0,046	0,049	0,030	1691
	Standard error	0,039	0,041	0,039	
	p- value	0,246	0,230	0,443	
Existence of inactivity periods	Effect	**0,101**	**0,099**	**0,112**	3087
	Standard error	0,026	0,026	0,026	
	p- value	0,000	0,000	0,000	
Number of inactivity periods	Effect	0,067	0,059	**0,106**	1099
	Standard error	0,049	0,050	0,048	
	p- value	0,172	0,245	0,028	
Existence of a revenue last month	Effect	0,002	0,004	-0,013	3087
	Standard error	0,026	0,026	0,024	
	p- value	0,948	0,882	0,605	
Last month revenue (Euros)	Effect	-48,319	-47,648	-52,766	2296
	Standard error	63,865	63,879	65,794	
	p- value	0,449	0,456	0,423	
Last month revenue is representative	Effect	-0,035	-0,033	*-0,044*	3087
	Standard error	0,028	0,028	0,027	
	p- value	0,208	0,236	0,096	
The household benefits from RMI	Effect	**0,028**	**0,027**	**0,034**	3087
	Standard error	0,012	0,012	0,013	
	p- value	0,023	0,028	0,008	
Subjective satisfaction degree of the professional career	Effect	**-0,463**	**-0,454**	**-0,517**	2967
	Standard error	0,159	0,163	0,145	
	p- value	0,004	0,005	0,000	
Missing revenue	Effect	*-0,016*	*-0,017*	-0,011	3087
	Standard error	0,009	0,009	0,010	
	p- value	0,078	0,064	0,270	
Less than 1200 euros	Effect	**0,079**	**0,078**	**0,081**	3087
	Standard error	0,023	0,023	0,022	
	p- value	0,001	0,001	0,000	
1200 to 1500	Effect	0,036	0,037	0,029	3087
	Standard error	0,028	0,028	0,026	
	p- value	0,187	0,181	0,260	
1500 to 4000	Effect	**-0,046**	**-0,047**	*-0,040*	3087
	Standard error	0,023	0,023	0,023	
	p- value	0,042	0,039	0,079	
More than 4000 euros	Effect	**-0,037**	**-0,037**	**-0,041**	3087
	Standard error	0,016	0,016	0,016	
	p- value	0,021	0,024	0,011	

Table 10- Men: effect of an accident, evaluation estimators

The standard errors of the evaluation estimators account for the first stage estimation of the Probit model.

	Statistics	Average treatment effect	Effect on the non treated	Effect on the treated	Obs.
Existence of long run unemployment periods (> 1 year)	Effet	*0,031*	*0,030*	**0,037**	2715
	Ecart-type	0,016	0,016	0,017	
	Proba. critique	0,051	0,068	0,026	
% of long run unemployment periods /total career	Effet	1,932	2,527	0,441	351
	Ecart-type	2,191	2,581	1,759	
	Proba. critique	0,378	0,328	0,802	
Existence of inactivity periods	Effet	0,005	0,005	0,004	2715
	Ecart-type	0,020	0,020	0,021	
	Proba. critique	0,805	0,795	0,841	
% of inactivity periods /total career	Effet	**2,711**	*2,642*	**2,911**	740
	Ecart-type	1,323	1,356	1,306	
	Proba. critique	0,040	0,051	0,026	
Existence of long employment periods (> 1 year)	Effet	-0,022	-0,022	-0,020	2715
	Ecart-type	0,015	0,016	0,014	
	Proba. critique	0,148	0,156	0,143	
% of long employment periods /total career	Effet	-1,117	-1,166	-0,969	2023
	Ecart-type	1,117	1,173	1,034	
	Proba. critique	0,317	0,320	0,349	
Existence of short employment periods (<= 1 year)	Effet	0,034	*0,036*	0,029	2715
	Ecart-type	0,021	0,022	0,021	
	Proba. critique	0,106	0,098	0,167	
% of short employment periods /total career	Effet	1,897	1,944	1,751	1839
	Ecart-type	1,578	1,682	1,380	
	Proba. critique	0,229	0,248	0,204	
Had been working last year	Effet	**-0,041**	**-0,039**	**-0,047**	2715
	Ecart-type	0,018	0,018	0,017	
	Proba. critique	0,020	0,034	0,004	
Number of hours worked last week	Effet	0,824	0,808	0,878	2228
	Ecart-type	0,603	0,618	0,586	
	Proba. critique	0,172	0,192	0,134	
Existence of long run unemployment periods	Effet	*0,029*	*0,028*	**0,035**	2715
	Ecart-type	0,016	0,016	0,017	
	Proba. critique	0,069	0,088	0,037	
Number of long run employment periods	Effet	**-0,134**	**-0,137**	*-0,125*	355
	Ecart-type	0,055	0,053	0,067	
	Proba. critique	0,015	0,010	0,062	
Existence of short employment periods	Effet	**0,042**	**0,043**	*0,036*	2715
	Ecart-type	0,021	0,021	0,020	
	Proba. critique	0,044	0,041	0,078	
Number of short employment periods	Effet	0,011	0,004	0,033	1826
	Ecart-type	0,049	0,049	0,050	
	Proba. critique	0,821	0,936	0,512	
Existence of long employment periods	Effet	-0,023	-0,024	-0,022	2715
	Ecart-type	0,015	0,016	0,014	
	Proba. critique	0,122	0,130	0,114	

The standard errors of the evaluation estimators account for the first stage estimation of the Probit model

(followed from table 10)	Statistique	Effet Global	Effet sur les non traités	Effet sur les traités	Obs.
Number of long run employment periods	Effet	0,027	0,025	0,034	2026
	Ecart-type	0,031	0,032	0,031	
	Proba. critique	0,384	0,438	0,271	
Existence of inactivity periods	Effet	0,003	0,003	0,002	2715
	Ecart-type	0,020	0,020	0,021	
	Proba. critique	0,885	0,870	0,938	
Number of inactivity periods	Effet	0,040	0,040	0,041	762
	Ecart-type	0,027	0,028	0,026	
	Proba. critique	0,139	0,154	0,120	
Existence of a revenue last month	Effet	-0,019	-0,019	-0,021	2715
	Ecart-type	0,017	0,018	0,017	
	Proba. critique	0,264	0,294	0,201	
Last month revenue (Euros)	Effet	*-141,489*	*-136,480*	*-157,997*	2281
	Ecart-type	78,159	78,021	83,239	
	Proba. critique	0,070	0,080	0,058	
Last month revenue is representative	Effet	-0,011	-0,008	-0,023	2715
	Ecart-type	0,021	0,022	0,021	
	Proba. critique	0,587	0,718	0,259	
The household benefits from RMI	Effet	0,003	0,004	0,002	2715
	Ecart-type	0,007	0,007	0,006	
	Proba. critique	0,604	0,586	0,693	
Subjective satisfaction degree of the professional career	Effet	-0,137	-0,156	-0,079	2599
	Ecart-type	0,110	0,114	0,103	
	Proba. critique	0,212	0,173	0,446	
Missing revenue	Effet	-0,001	-0,001	0,001	2715
	Ecart-type	0,009	0,009	0,009	
	Proba. critique	0,950	0,918	0,937	
Less than 1200 euros	Effet	**0,041**	**0,040**	**0,044**	2715
	Ecart-type	0,016	0,016	0,016	
	Proba. critique	0,010	0,014	0,004	
1200 to 1500	Effet	-0,021	-0,024	-0,011	2715
	Ecart-type	0,022	0,022	0,022	
	Proba. critique	0,338	0,276	0,627	
1500 to 4000	Effet	-0,011	-0,009	-0,018	2715
	Ecart-type	0,021	0,021	0,021	
	Proba. critique	0,588	0,665	0,379	
More than 4000 euros	Effet	-0,008	-0,005	-0,016	2715
	Ecart-type	0,015	0,016	0,014	
	Proba. critique	0,615	0,745	0,266	