Working conditions and work-related chronic diseases: A career-long retrospective study

THOMAS BARNAY[a,b] and ÉRIC DEFEBVRE[b,1]

[a] *Créam, Rouen University*

[b] *Érudite, Paris-Est Créteil University (Upec) and Tepp FR n°3435-CNRS*

Work in progress (November 2015)

Work in progress – Do not quote

Abstract: Our goal is to estimate the impact of working conditions on the declaration of chronic diseases in France. Based on a rebuilt retrospective, lifelong panel, we use a mixed econometric strategy relying on Difference in differences with a matching method taking into account the endogeneity of working conditions as well as unobserved heterogeneity. We define different treatment variables including the simultaneity and duration of exposure to both physical and psychosocial working conditions. Our main results are as follow. Men are much more exposed than women to detrimental physical working conditions (but both are equally exposed to psychosocial working conditions), but the latter experience the biggest impact on their self-reported chronic diseases. For women, we find an effect of exposure on chronic diseases after the exposure to physical and psychosocial working conditions. In men, we find an impact of psychosocial exposure on their declaration of chronic diseases, but no effect of physical strains.

JEL classifications: J81; I14; C32

Key words: working conditions; chronic diseases; difference in differences; matching

[1] *Correspondence to: Érudite, Paris-Est Créteil University, 61 avenue du Général de Gaulle, 94010 Créteil, France. Mail: eric.defebvre@univ-paris-est.fr. Phone: +33 651775786.*

1. Introduction

Since 2003, the working conditions issue has been discussed between the social partners and the French government. A law, implemented early 2015 in France, fits into this logic offering the access to training programs in order to change job, or the opportunity to retire earlier for exposed workers. In a fast-moving world in terms of new technologies, management methods, activity controls (quality standards, processes rationalization, *etc.*) as well as contacts with the public confront employees with different and increased work pressures (Askénazy *et al.*, 2006), the question of working conditions become even more acute.

Physical working conditions such as night time, repetitive work, physical load as well as work environment have been widely studied in the literature. In addition to these constraints, other indicators are being used to assess working conditions. One can distinguish two main categories: strains related to the organization and psychosocial risk factors. The literature shows obvious impacts on workers' health status of these working conditions. However, few studies tackle the methodological difficulties that are endogeneity biases coming from the selection into the labour market. These biases are related to baseline characteristics and unobserved heterogeneity.

In this study, we work on a sample of 5,000 individuals coming from the Health and Professional Route French survey (*Santé et Itinéraire Professionnel* – Sip). We use a Difference in differences methodology combined with matching methods allowing us to take into account the endogeneity of working conditions and unobserved heterogeneity. We can reconstruct for each year since the entry into the labour market, the number and the nature of exposures. We can also measure the duration of each of them.

At first, we make a brief overview of the literature about indicators of working conditions and their impact on individuals' health status. We then present our data, methodology and results. Finally, we discuss these results.

2. Short literature review

2.1. Working conditions indicators

Physical working conditions such as night time work, repetitive work, physical load as well as work environment have been widely analyzed in the literature. Work environment embodies elements such as being exposed to hazardous materials, to unusual temperatures and moisture, to noise, vibrations, light *etc.* Men are usually the ones being exposed the most to such conditions (Fletcher *et al.*, 2010).

In addition to physical constraints, other indicators can be used to highlight the working conditions. These are classified into two main categories: strains related to the organization of work and based on objective factors, and psychosocial risk factors linked with the psychological burden of work, based on employees' feelings (Bué *et al.*, 2008). As far as organization of work is concerned, items related to contractual aspects of work such as its nature (Charbotel *et al.*, 2009; Robone *et al.*, 2011), private life/professional life conflicts (Hammer *et al.*, 2004), changes in the contract (Blanchet *et al.*, 2007; Robone, *ibid.*) as well as its termination (Pisljar *et al.*, 2011; Debrand *et al.*, 2007) have often been discussed in the literature. Many indicators also address the temporal dimension of work: long working hours (Cottini *et al.*, 2013; Kaikkonen *et al.*, 2009), atypical hours such as night work (Harrington, 2001), overtime (Pisljar *et al.*, *ibid.*; Robone *et al.*, *ibid.*) and changes in schedules (Askénazy *et al.*, 2006) are potentially harmful to workers. A final category focuses on intensive work indicators. Thus, having an intensive work resulting in heavy workload, repetitive tasks or shifts in tasks is also likely to create tensions for the employees (Cottini *et al.*, *ibid.*).

The indicators used in the field of psychosocial risks at work are much less numerous but more hierarchical in the literature. Working conditions have been defined in seminal sociological and psychological papers. In particular, the Job Demand-Control (JD-C) Model, that is the imbalance model between perceived pressure (demand) and decision latitude (level of control), refers to concepts of decision latitude, job demands and job strains (Karasek, 1979; Theorell and Karasek, 1996). Job Demands is an aggregate of several criteria describing the degree of interest, the quantity and the difficulty of the work the employee has to handle, and also the possibility to manage his family life with his job sphere. Decisional Latitude or Job Control describes the possibility for a worker to decide how to conduct his activity. The third aspect of the Karasek Model, implemented by Johnson (Johnson, 1988), is the level of psychological support provided by colleagues and hierarchy. Siegrist's model (1996), on the other hand, introduces Effort-Reward-Imbalance (ERI). Rewards are provided to employees by three potential channels: money (*i.e.*, adequate salary), esteem (*e.g.* respect and support) and security/career opportunities (*e.g.* promotion prospects, job and employment status securities).

2.2.The impact of working conditions on health

Being exposed to night work or doing a repetitive or physically demanding work has an effect on the declaration of limitations. Having a physically demanding work is also known to impact the self-rated health of workers (Debrand *et al.*, 2008). Work environment has an influence on the health of workers too. In a study on US workers , the impact of having detrimental environmental working conditions (being exposed to the weather, extreme temperatures or moisture) impacts young worker's self-rated health status, with a slightly less important effect for women (Fletcher *et al.*, *ibid.*). The exposure to hazardous materials also increases activity limitations in 50-59 year-old workers (Bahu *et al.*, 2011).

Mental health is also affected by working conditions. The atypical employment contracts such as imposed part-time work increase the occurrence of depressive symptoms among employees (Santin *et al.*, 2009). Cottini *et al.* (*ibid.*), using EWCS data (waves 1995, 2000, 2005) on 15 EU countries find that job quality (in particular job demands) affect mental health. Bildt *et al.* (2002) also show that exposure to difficult working conditions may have an adverse effect on mental health, with differences according to gender. Men are more affected by changes in tasks and a lack of pride at work. Among women, other determinants explain this effect, such as no training, low motivation and weak social support at work. Men suffer from the omnipresence of work in their lives and the repetitiveness and lack of cooperation in the labour force. Women, in addition to the repetitive nature of tasks and lack of cooperation, identify starting work before age 18 and involuntary interruptions during work as criteria impacting their health. Other gender-linked factors are highlighted by Cohidon *et al.* (2010) as determinants of mental health such as contact with the public (men). Using Karasek (1979) and Johnson *et al.* (1989) models, Laaksonen *et al.* (2006) show that stress at work, job demand, weak job decision, lack of justice and support induce bad health.

2.3.Biases in the relation

In order to identify the specific effect of working conditions on health, it is necessary to control for the endogeneity biases, because the choice of a job is unlikely a random experience (due to heterogeneity of individual preferences, risk aversion attitudes, working conditions and health status among the population). This choice is also made based on initial health status, resulting in a biased relationship due to reverse causality. Very few papers tried to handle this endogeneity bias. Notably, Cottini and Lucifora (*op.cit.*) implemented an Instrumental Variable strategy relying on variations across countries in terms of workplace health and safety regulation in order to identify the causal effect of detrimental working conditions on mental health. Most of the time, because of the lack of data available and the difficulty to find accurate instruments for working conditions, the question of endogeneity is eluded in the literature.

3. Data

We use data coming from the Health and Professional Route French survey (*Santé et Itinéraire Professionnel* – Sip). It has been designed jointly by the statistical departments of French ministries of Health[2] and Labor[3]. As of today, the panel is composed of two waves: one in 2006 and one in 2010, both being conducted on the same sample of individuals aged 19-74 in 2006 and with the same questions[4]. Two questionnaires are proposed: the first one is administered directly by an interviewer and investigates the individual characteristics, health and employment status. It also contains a grid allowing the reconstruction of a biography of the individual's life: his/her childhood, education, health, professional route and working conditions as well as the significant events of his/her life. The second one is a self-administered questionnaire which focuses on more sensitive elements, such as health-related risky behaviors (weight, alcohol and tobacco consumption). Overall, more than 13,000 individuals have been interviewed in 2006 and more than 11,000 of them in 2010 as well, making this panel survey representative of the French population.

We make specific use of the biographic dimension of the 2006 survey by reconstructing the individuals' career and health events yearly. We are therefore able to know, for each individual, his/her employment status, working conditions and health-related problems every year from their childhood to the date of the survey. As far as working conditions are concerned, the survey provides information about ten indicators of exposure: night work, repetitive work, physical load and exposure to toxic materials, as well as full skill usage, work under pressure, tensions with the public, reward, conciliation between work and family life and relationships with colleagues. The intensity of exposure to these work strains is also known. Individuals' health statuses are assessed by their declaration of chronic diseasesfor which the onset and end dates are available.

In our study, we are working on this reconstructed longitudinal retrospective dataset, composed of more than 5,000 individuals, with their career and health-related data available from their childhood to the year of the survey (ranging from 1930 to 2006). Thus, the final sample we are working on is composed of around 2,500 men and 2,500 women, for whom we have complete information of.

---

[2] *Directorate for Research, Studies, Assessment and Statistics (Drees) – Ministry of Health.*
[3] *Directorate for Research, Studies and Statistics (Dares) – Ministry of Labor.*
[4] *Following recommendations coming from the College of expertise on the statistical monitoring of psychosocial risks at work, the 2010 wave received an improvement about the assessment of psychosocial risk factors.*

4. Empirical analysis

4.1. Difference in Differences general framework

The objective of a Difference in differences methodology is to handle the individual and temporal heterogeneities that may bias our estimations of the impact of working conditions on chronic diseases: the choice of a job depends on a lot of unobserved individual characteristics, such as individual preferences, risk aversion behaviors, as well as elements related to the initial health capital. These elements, being unaccounted for, are likely to be linked to individuals' health status as well as working conditions (endogeneous sorting on the labor market - Cottini *et al.*, 2013), hence representing several endogeneity sources in our study. This situation can be described, using the following model:

$$y_{i,t} = \alpha T_i + \gamma_i + \delta_{i,t} + \mu_{i,t} \quad (1)$$

Where $y_{i,t}$ is the outcome and $\mu_{i,t}$ the error term, both depending on individual i and time t. The Difference in differences method consists of two main steps. The first one has the objective to handle the non-time dependant unobserved individual heterogeneity (γ_i) existing in the two groups (treated and non-treated) using panel data and by doing a temporal difference between two periods of time: one before the treatment ($t-1$) and one after the treatment ($t+1$).

The second one aims at suppressing the unobserved time-dependant (but group-fixed) heterogeneity ($\delta_{i,t}$) by doing a difference between the results obtained in first difference for the treated and non-treated populations.

$$\left(y_{i,t+1} - y_{i,t-1}\right) - \left(y_{j,t+1} - y_{j,t-1}\right) =$$
$$\alpha T_i + \left[\left(\delta_{i,t+1} - \delta_{i,t-1}\right) - \left(\delta_{j,t+1} - \delta_{j,t-1}\right)\right] + \left[\left(\mu_{i,t+1} - \mu_{i,t-1}\right) - \left(\mu_{j,t+1} - \mu_{j,t-1}\right)\right] \quad (2)$$

The validity of this modelisation is based on the Conditional Independence Assumption (CIA, also known as *Common Trend*), stating that the outcome of the treated population would have been the same as the one of the non-treated population, in case the former would not have been treated. If this (rather strong) assumption is not verified as is, which is likely to be the case, the estimations are at risk to be biased by group- and time-dependant heterogeneity, formally inducing:

$$\left(\delta_{i,t+1} - \delta_{i,t-1}\right) - \left(\delta_{j,t+1} - \delta_{j,t-1}\right) \neq 0 \quad (3)$$

Even though the determination of the two groups (treated and non-treated) is often made *ad hoc*, it is possible (or even important, considering the assumption previously mentioned) to wisely build them (Givord, 2010), so that the differences existing between the two populations in terms of health status are reduced *ex-ante* as much as possible. This can be done, notably by using specific pre-treatment observable variables and matching methods, prior to the Difference in differences, so that the CIA assumption may hold, conditionally to these observables.

4.2.Matching method

To reduce individual heterogeneity between treated and non treated groups, we perform a matching method. We implement a Coarsened Exact Matching method (CEM, Blackwell *et al.*, 2011). The main objective of this methodology is to allow the reduction of imbalance (one covariate at a time) and global imbalance (every covariates at the same time - Iacus *et al.*, 2008) between the treated and the non-treated groups (according to several pre-treatment covariates), in order to obtain better counterfactuals and therefore more reliable results (this should make the CIA assumption less of a concern). CEM offers an advantage compared to other matching methods: it helps coping effectively with the *curse of dimensionality*. Coarsening variables in their areas of common empirical support increases the number of possible counterfactuals for each observation in the treated group, and therefore decreases the number of discarded observations due to the lack of matches. In addition, CEM reduces the model choice dependence of the results (Iacus *et al.*, *ibid*). Yet, this particular matching method is still demanding in terms of sample size, and only pre-treatment variables (*i.e.* variables determined before the exposure to detrimental working conditions) must be chosen.

4.3.Estimation in our study

Practically, we perform the Difference in differences by simple linear regressions using the Ordinary Least Squares estimator (panel models can also be used, even though those are often found to have very similar results) of the following model, explaining chronic diseases (y_i):

$$y_i = \beta_0 + \beta_1 Period_i + \beta_2 T_i + \beta_3 Period_i T_i + \epsilon_i \quad (4)$$

where $Period_i$ is the indicator of the time period (0 for baseline, 1 for follow-up), T_i is a dummy variable for the treatment (0 for the non-treated, 1 for the treated), $Period_i T_i$ (variable of interest) is the cross variable including periods and treatment and β_1, β_2 and β_3 are their respective coefficients. The error term is denoted ϵ_i. The estimation of this model is weighted, accordingly to the results of the prior matching method.

5. Variables of interest

5.1. Working conditions: definition of a treatment

We use ten individual and annual indicators to assess the exposure to detrimental working conditions: night work, repetitive work, physical load and exposure to toxic materials, full skill usage, working under pressure, tensions with the public, reward, conciliation between work and family life and relationships with colleagues. For each indicator, individuals must indicate if they “Always”, “Often”, “Sometimes” or “Never” faced it during this period: we consider one individual to be exposed if he/she “Always” faced the said work strain, to make-up for the declarative nature of our data.

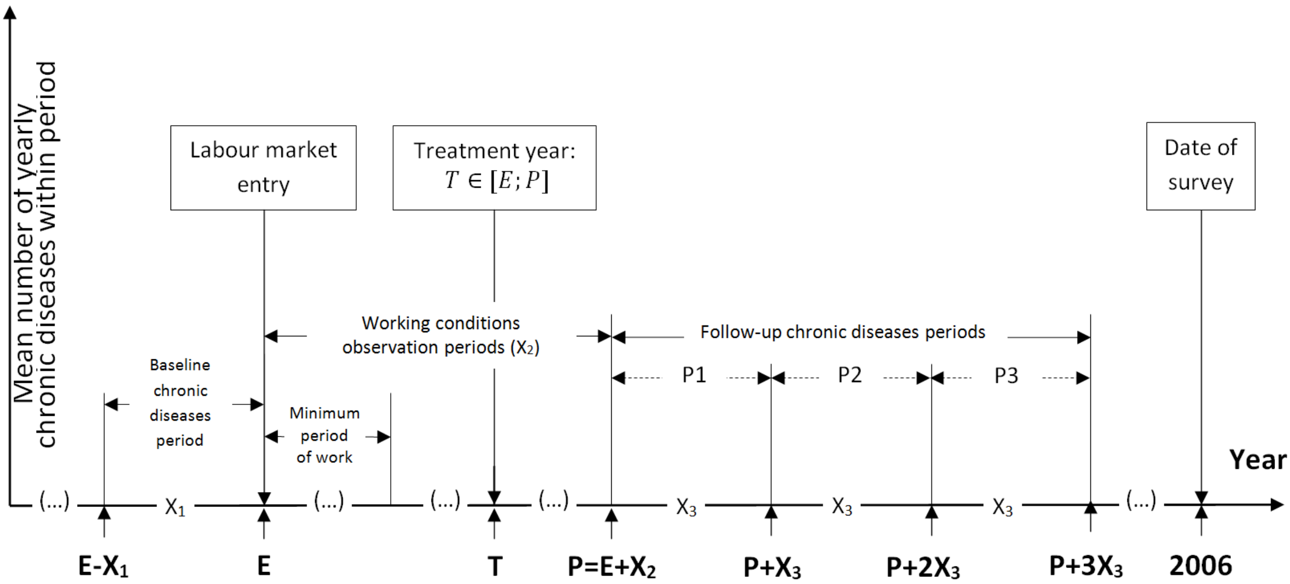
Following the literature on working conditions and to better assess the impact of these indicators on health status, we grouped them into two relevant classes. The first one regroups the physical strains of work, and is composed of the night work, repetitive work, physical load and exposure to toxic materials indicators. The second one regroups the psychosocial risk factors: full skill usage, working under pressure, tensions with the public, reward, conciliation between work and family life and relationships with colleagues. In order to take into account for the potentiality of cumulative effects between strains, we considered two kinds of exposures: single exposures (when the individual faced only one strain at a time each year) and poly exposures (if the individual faced two or more strains simultaneously each year). Then, the duration of exposure has been accounted for by introducing varying minimum durations of exposure.

To allow for more homogeneity and robustness of our treatment variables, we observe the exposure to detrimental working conditions within a dedicated observation period (going from E to P, as denoted in Figure 1 below), starting at the beginning of individuals' careers (E) and lasting for a certain amount of years (X_2, depending on the varying thresholds of exposure). In order for someone to be a treated, he must reach the treatment thresholds within this observation period (the other ones are considered non-treated). Doing so allows us to make sure exposure years cannot be too spread up. Also, we considered treated/non-treated individuals having worked at least a fraction of the observation period, the size of it depending on the treatment thresholds too: people who did not work this fraction of time are considered too specific in terms of labour market and health behaviours, hence not really comparable to the other ones.

5.2. Chronic diseases

Our dependant variable is based on the annual number of chronic diseases (only accidents, handicaps and chronic diseases can be reconstructed year by year, and to avoid mixing-up too different types of indicators we chose to keep only the latter): a chronic disease is intended, in the Sip survey, as an illness that lasts or will last for a long time, or an illness returning regularly. Allergies such as hay fever or the flu are not considered chronic diseases. This definition is definitely broader than the administrative definition. This indicator is available from childhood to the date of the survey. Figure 1 explains the construction of our dynamic health status indicator, plus the exposure observation period described above.

Figure 1: Observation and chronic disease periods setup



Source: *Authors.*

In Figure 1, we estimate the mean number of yearly chronic diseases from a baseline period (X_1) occurring before the entry in the labour market to the date of survey (2006). E is the year of entry in the labour market for individual i, and T is his/her year of treatment (for the treated).

The chronic diseases indicator is defined on four periods of time ($baseline, P_1, P_2$ and P_3) as follow (the X_i durations are parameters we can choose, according to the situation- it will be defined in details later):

- The baseline chronic diseases period (which represents the baseline health capital of each individual) is the mean number of current yearly chronic diseases within the X_1 years before labour market entry (from $E - X_1$ to E). It allows to take into account the initial health conditions during the X_1 period.
- The second period (X_2) starts with the beginning of the working age (E) and ends at year P. Starting from E, the individual can be in various occupational statuses such as employment or unemployment. If the individual is at work, he can be exposed to working conditions. As described in part 5.1, we introduced a minimum duration at work (of a certain duration of years, depending on the needs described later) that the individual must reach in order to be selected in our sample, which is also represented in this graph.
- The three outcomes ($P_t, t \in [1;3]$) of chronic diseases, starting after the end of the exposure observation period ($P = E + X_2$), are the mean numbers of current yearly chronic diseases within the t^{th} X_3-year interval following P (from P to $P + X_3$ for P_1, …, from $P_1 + X_3$ to $P_2 + X_3$ for P_3). We did not choose to start these three periods right after the individual reaches the treatment, because it would force us to compare these individuals with non-treated who, by definition, do not reach the treatment requirements, inducing a difference in the years of observation for chronic diseases.

The objective is to be able to compare the baseline chronic diseases (before any possible exposure to detrimental working conditions) to three periods of follow-up health status (happening after the end of the observation period for treated and non-treated), in order to have the short/mid/long-term effects of work strains on the declaration of chronic diseases.

5.3 Matching variables

As for the matching method, we need to choose variables that are relevant in terms of health status and determination in the labour market, as well as helping to meet the CIA requirement. These variables must also not be influenced by the treatment (so they should happen before it). We matched our individuals according to their gender (as described in Shmueli 2003 and Devaux *et al.* 2008, men and women do not have the same declarative patterns about health and labour market outcomes), their education (four levels: no diploma, inferior to bachelor degree, equivalent to bachelor degree and superior to bachelor degree) and important events happening during childhood (heavy health problem of relatives, death of relatives, separation from one or more parent, violence suffered from relatives, violence at school or in the neighbourhood, family conflicts and poor material living conditions), as it is pretty clear that such childhood events may impact the early outcomes in terms of health status and labour market status.

At this point, the addition of more matching variables may decrease our sample to a critical size (*curse of dimensionality*).

5.4. Thresholds determination process

One of the most important point about working conditions is to assess their impact according to the duration and cumulative processes. Indeed, in this context, the determination of treatment thresholds is key. We designed nine progressive exposure patterns, in order to assess potentially varying effects of health status of different levels of exposure. Therefore, changing the treatments thresholds will, as a consequence, lead to other changes in the parameters, notably the exposure observation period and the minimum duration at work within it. The health observation periods (baseline and the three follow-ups) may also vary in duration: doing one-year periods may expose us to choosing too specific years, so one might prefer doing two plus-year periods instead.

Table I: Iterations description

Iteration Parameter	i1	i2	i3	i4	i5	i6	i7	i8	i9
Treatment variable									
Mono-exposure threshold	4	6	8	10	12	14	16	18	20
Poly-exposure threshold	2	3	4	5	6	7	8	9	10
Periods definition									
(X_2) Working conditions observation period	6	9	12	15	18	21	24	25*	25*
Minimum duration at work	2	3	4	5	6	7	8	9	10
(X_1) Baseline chronic diseases period duration	2								
(X_3) Follow-up chronic diseases periods duration									

Indications: *in years. *: the pattern for i8 and i9 about the exposure observation period has been altered, in order to ensure a decent sample size. Hence, the observation period has been capped to a maximum of 25 years instead of 27 and 30, respectively for i8 and i9.*
Reading: *for the fourth iteration (i4), an individual must reach 10 years of mono-exposure or 5 years of poly-exposure within the 15 years after the labour market entry to be considered a treated. Also, he/she must have worked at least 5 years within this period to be retained in our sample. His/her health status will be assessed by the mean number of yearly chronic diseases at baseline (the 2 years before labour market entry), and three more times (follow-up) after the end of the working conditions observation period (P_1: the 2 years right after; P_2: the two years after P_1; P_3: the 2 years after P_2).*
Source: *Authors.*

The nine iterations are designed according to increasing levels of exposures to detrimental working conditions. The pattern we followed is 2 years more of single exposures from an iteration to another. Poly-exposure durations are half the one of mono-exposure (inspired by the law of January 2015 about working conditions in France: poly-exposures, *i.e.* 2 or more simultaneous exposures, grants twice as much points compared to single-exposures in the pension calculations). The durations of the exposure observation periods is determined so that it lets a decent amount of years for the individuals to reach the treatment thresholds (three half the maximum duration of exposure needed to be a treated, *i.e.* three half of the mono-exposure threshold). The minimum duration at work during the observation period is set as the minimum exposure threshold to be a treated, *i.e.* it equals the poly-exposure threshold (the goal is to have homogeneous individuals while avoiding to lose too many of them in the sample). As for the durations of health status periods, we chose to make them two-year long, in order to avoid isolated specific years (as described earlier), but also to preserve the sample size as much as possible (the longer the periods, the longer the time horizon needed, the less the individuals meeting such requirements, plus we work on chronic diseases, which are not so volatile).

6. Results

6.1.Descriptive statistics

6.1.1.Sample description

The following descriptive statistics are made on the sixth iteration of our sample. As seen in Table II, our sample is composed of 50.69% of women. The mean age of the sample is 58, which is not surprising, considering the time span necessary to conduct our methodology for i6 (see Figure 1). For the most part their level of education is of secondary level (61.42%), with few people having a primary, superior or bachelor degree level of education (around 12% each). Also, as anticipated, the level of education impacts the labour entry year by quite a margin.

Table II: Sample descriptive statistics

Variables	Percentage
Gender	
Men	49.31
Women	50.69
Age (2006, mean)	58.27
Education	
Primary	12.14
Secondary	61.42
Bachelor degree	12.46
Superior	12.28
Mean labour market entry year	
General	1965
Primary education	1960
Secondary education	1964
Bachelor degree	1968
Superior	1970

Interpretation: *Our sample is composed of 49.31% of men and 50.69% of women.*
Field: *Population aged 20-74 in 2006. 6th iteration.*
Source: *Sip (2006).*

6.1.2.Treatment description

30.77% (*resp.* 19.33%) of our sample is considered as physically (*resp.* psychosocially) treated, with mean years of treatment being higher for the psychosocial treatment (Table III). With no surprise, men are the ones being the most exposed to the physical treatment (37.84%), when the gender repartition tends to be more balanced (19.80% in men, 18.87% in women) for the psychosocial treatment. As expected, the level of exposure and the nature of detrimental working conditions differs depending on the level of education: physically treated individuals are mostly people with a primary (45.45%) or secondary (34.65%) levels of education. The psychosocial treatment is, once again, more widespread as 22.20% (*resp.* 19.11%, 19.25% and 17.30%) of people having a primary (*resp.* secondary, bachelor degree and superior) levels of education are considered as psychosocially treated.

Table III: Treatment descriptive statistics

Variables	Percentage	
	Physical treatment	Psychosocial treatment
Prevalence	30.77	19.33
Mean year of treatment	1977	1981
Gender		
Men	37.84	19.80
Women	23.89	18.87
Education		
Primary	45.45	22.20
Secondary	34.65	19.11
BAC	15.48	19.25
Superior	12.07	17.30

Interpretation: *37.84% of men and 23.89% of women are exposed enough to detrimental physical working conditions to be considered treated.*
Field: *Population aged 20-74 in 2006. 6th iteration.*
Source: *Sip (2006).*

6.1.3.Outcome description

Tables IV below shows descriptive statistics for the outcome variable. Logically, the mean number of chronic diseases on our sample increases as the periods go (from 0.13 for the 2 years before labour market entry to 0.74 at P_3. The difference of mean number of chronic diseases between men and women gets bigger over time too. Interestingly, the more educated population suffers from more chronic diseases. But the most interesting intuition given by the description of the sample is probably the repartition of chronic diseases over time between treated and non-treated populations: we indeed find that our treated population starts with a significantly lower mean number of chronic diseases for future physically treated individuals (0.10 *vs.* 0.14), hence inducing some sort of (self) selection on the labor market, linked to initial health status (endogeneous selection). No such relationship is to be found in the future psychosocially treated population. This difference stabilizes over time, but always indicates a better health status for the treated population. Our psychosocial treatment, on the other hand, describes a treated population being increasingly in worse health status than the non-treated.

Table IV: Health status, by periods

Variables	Periods			
	Initial	P1	P2	P3
Mean	0.13	0.57	0.65	0.74
Gender				
Men	0.11	0.52	0.58	0.66
Women	0.15	0.63	0.72	0.82
Education				
Primary	0.12	0.48	0.54	0.61
Secondary	0.11	0.54	0.62	0.72
Bachelor degree	0.18	0.71	0.79	0.86
Superior	0.21	0.71	0.80	0.89
Physical Treatment				
Treated	0.10	0.56	0.63	0.73
Non treated	0.14	0.58	0.66	0.74
Psychosocial Treatment				
Treated	0.14	0.69	0.79	0.89
Non treated	0.13	0.54	0.62	0.70

Interpretation: *the treated (physical) population has a mean of 0.32 chronic disease in period 1 while the non-treated population has a mean of 0.34.*
Field: *Population aged 20-74 in 2006. 6th iteration.*
Source: *Sip (2006).*

Obviously, this last result prompts us to investigate deeper into this matter, while taking good care of this health-related selection process. More precisely, there is a need to confirm or not that this unexpected difference in health statuses between treated and non-treated populations is reliable.

6.2. General econometric results

The results for iterations 1, 3, 6 and 9 are shown in tables V, VI, VII and VIII below[5]. In these tables, first are shown the results for the baseline chronic diseases differences between treated and non-treated, then the follow-up differences and last the difference-in-differences (standard errors in italics). As demonstrated by the unmatched baseline differences, there were often statistically significant differences between future physically treated and non-treated, indicating that the future treated declared less chronic diseases, which do not appear to be the case for the psychosocial treatment.

The follow-up differences indicate that the degradation trend of the treated population's chronic diseases tends to be more important than the one of our non-treated population, possibly showing the impact of the exposure to detrimental working conditions. These results plead for the endogeneous selection on the labour market hypothesis, stating that people are likely to choose their job considering their own initial health status, and in any case justify an approach that takes into account this possibility. We tried to minimize this selection process using a matching method prior to the difference in differences models. As we can see, our matching method systematically succeeds in reducing the baseline differences in terms of chronic diseases declaration (*e.g.* in Table V for the male population and physical treatment, the unmatched baseline difference is $-0{,}031*$ whereas the matched one becomes non-significant). In addition, the follow-up differences are reduced too, which may indicate that the CIA assumption is most likely better fulfilled. It is to be noted that the selection process according to several observable characteristics seems to act differently depending on the nature of the treatment. While people with less baseline chronic diseases prefer/are preferred for physical jobs, there is no significant difference in chronic diseases between future psychosocially treated and non-treated. This can be seen in the follow-up differences as well: the psychosocial follow-ups decrease when making use of a matching methods (*e.g.* in Table VI, the first follow-up difference for every period P_i in women is highly significant in unmatched samples when it becomes non-significant after matching).

[5] Other iterations show very similar results, in terms of trend.

Table V: Results of the Difference in Differences models (i1)

Treatment /Gender	Baseline (first difference)		Follow-up (first difference)		Diff-in-Diff		N (Treat./Tot.)
	Diff.	Std. error	Diff.	Std. error	Diff.	Std. error	
UNMATCHED SAMPLE: Physical treatment							
Men							
P1	-0.031*	*0.018*	-0.013	*0.025*	0.018	*0.031*	956/2374
P2			-0.007	*0.027*	0.024	*0.032*	
P3			0.003	*0.029*	0.034	*0.034*	
Women							
P1	-0.016	*0.021*	0.043	*0.030*	0.059	*0.037*	871/2790
P2			0.044	*0.032*	0.060	*0.038*	
P3			0.031	*0.035*	0.047	*0.040*	
MATCHED SAMPLE: Physical treatment							
Men							
P1	-0.027	*0.021*	-0.002	*0.029*	0.025	*0.036*	926/2259
P2			0.010	*0.030*	0.037	*0.037*	
P3			0.030	*0.032*	0.057	*0.038*	
Women							
P1	-0.015	*0.023*	0.055	*0.034*	0.070*	*0.041*	847/2606
P2			0.056	*0.036*	0.070*	*0.043*	
P3			0.049	*0.038*	0.063	*0.045*	
UNMATCHED SAMPLE: Psychosocial treatment							
Men							
P1	0.019	*0.020*	0.059**	*0.028*	0.041	*0.034*	639/2374
P2			0.057*	*0.030*	0.038	*0.036*	
P3			0.060*	*0.032*	0.041	*0.038*	
Women							
P1	0.046**	*0.021*	0.122***	*0.031*	0.076**	*0.038*	817/2790
P2			0.125***	*0.033*	0.080**	*0.040*	
P3			0.105***	*0.036*	0.059	*0.042*	
MATCHED SAMPLE: Psychosocial treatment							
Men							
P1	-0.021	*0.025*	0.009	*0.035*	0.030	*0.043*	623/2285
P2			0.005	*0.036*	0.025	*0.044*	
P3			-0.003	*0.039*	0.018	*0.046*	
Women							
P1	0.024	*0.023*	0.090***	*0.033*	0.066	*0.040*	792/2654
P2			0.091***	*0.035*	0.067	*0.042*	
P3			0.069*	*0.038*	0.045	*0.044*	

Interpretation: ****: significant at the 1% level, **: significant at the 5% level, *: significant at the 10% level.*
Reading: *the first two columns show the results for the baseline differences between treated and non-treated, the next two the ones for the different follow-ups periods (P_i), and the two last the difference between these two differences (i.e. the difference between treated and non-treated at follow-up, minus the difference between treated and non-treated at baseline). Results are shown for men and women, physical and psychosocial treatments and matched and unmatched differences.*
Field: *Population aged 20-74 in 2006. First iteration: 4 years of mono-exposure / 2 years of poly -exposure thresholds, 6-year observation period, 2 years minimum at work.*
Source: *Sip (2006).*

Table VI: Results of the Difference in Differences models (i3)

Treatment /Gender	Baseline (first difference)		Follow-up (first difference)		Diff-in-Diff		N (Treat./Tot.)
	Diff.	Std. error	Diff.	Std. error	Diff.	Std. error	
UNMATCHED SAMPLE: Physical treatment							
Men							
P1	-0.035**	*0.017*	-0.036	*0.029*	-0.001	*0.034*	883/2297
P2			-0.043	*0.031*	-0.008	*0.036*	
P3			-0.047	*0.033*	-0.012	*0.037*	
Women							
P1	-0.041**	*0.019*	0.016	*0.037*	0.057	*0.042*	705/2612
P2			0.024	*0.041*	0.065	*0.045*	
P3			0.040	*0.044*	0.081*	*0.047*	
MATCHED SAMPLE: Physical treatment							
Men							
P1	-0.022	*0.018*	-0.002	*0.031*	0.019	*0.036*	859/2149
P2			-0.007	*0.034*	0.015	*0.038*	
P3			-0.012	*0.036*	0.010	*0.040*	
Women							
P1	-0.029	*0.020*	0.026	*0.039*	0.055	*0.044*	689/2431
P2			0.033	*0.043*	0.062	*0.048*	
P3			0.047	*0.046*	0.076	*0.050*	
UNMATCHED SAMPLE: Psychosocial treatment							
Men							
P1	0.027	*0.021*	0.049	*0.034*	0.022	*0.040*	530/2297
P2			0.045	*0.036*	0.018	*0.041*	
P3			0.040	*0.038*	0.013	*0.043*	
Women							
P1	0.031	*0.020*	0.123***	*0.039*	0.092**	*0.044*	620/2612
P2			0.108***	*0.041*	0.077*	*0.046*	
P3			0.130***	*0.044*	0.099**	*0.049*	
MATCHED SAMPLE: Psychosocial treatment							
Men							
P1	0.003	*0.023*	0.018	*0.038*	0.015	*0.044*	513/2135
P2			0.014	*0.040*	0.011	*0.046*	
P3			0.003	*0.042*	-0.001	*0.047*	
Women							
P1	0.008	*0.022*	0.069	*0.043*	0.062	*0.048*	602/2480
P2			0.043	*0.046*	0.035	*0.051*	
P3			0.068	*0.049*	0.060	*0.053*	

Interpretation: ****: significant at the 1% level, **: significant at the 5% level, *: significant at the 10% level.*
Reading: *the first two columns show the results for the baseline differences between treated and non-treated, the next two the ones for the different follow-ups periods (P_i), and the two last the difference between these two differences (i.e. the difference between treated and non-treated at follow-up, minus the difference between treated and non-treated at baseline). Results are shown for men and women, physical and psychosocial treatments and matched and unmatched differences.*
Field: *Population aged 20-74 in 2006. Third iteration: 8 years of mono-exposure / 4 years of poly -exposure thresholds, 12-year observation period, 4 years minimum at work.*
Source: *Sip (2006).*

Table VII: Results of the Difference in Differences models (i6)

Treatment /Gender	Baseline (first difference)		Follow-up (first difference)		Diff-in-Diff		N (Treat./Tot.)
	Diff.	Std. error	Diff.	Std. error	Diff.	Std. error	
UNMATCHED SAMPLE: Physical treatment							
Men							
P1	-0.035**	*0.015*	-0.028	*0.038*	0.006	*0.041*	755/1995
P2			-0.031	*0.040*	0.004	*0.043*	
P3			-0.027	*0.043*	0.008	*0.045*	
Women							
P1	-0.052***	*0.018*	0.035	*0.050*	0.087	*0.053*	490/2051
P2			0.044	*0.053*	0.096*	*0.056*	
P3			0.058	*0.057*	0.110*	*0.060*	
MATCHED SAMPLE: Physical treatment							
Men							
P1	-0.018	*0.016*	0.012	*0.040*	0.030	*0.043*	736/1878
P2			0.009	*0.043*	0.027	*0.046*	
P3			0.015	*0.045*	0.033	*0.048*	
Women							
P1	-0.029	*0.018*	0.074	*0.053*	0.104*	*0.056*	477/1864
P2			0.083	*0.056*	0.113*	*0.059*	
P3			0.094	*0.061*	0.123*	*0.064*	
UNMATCHED SAMPLE: Psychosocial treatment							
Men							
P1	0.009	*0.020*	0.142***	*0.050*	0.134**	*0.054*	395/1995
P2			0.150***	*0.055*	0.142**	*0.059*	
P3			0.163***	*0.059*	0.154**	*0.062*	
Women							
P1	0.014	*0.022*	0.158***	*0.057*	0.144**	*0.061*	387/2051
P2			0.195***	*0.061*	0.182***	*0.065*	
P3			0.224***	*0.065*	0.210***	*0.069*	
MATCHED SAMPLE: Psychosocial treatment							
Men							
P1	-0.001	*0.024*	0.102*	*0.057*	0.103*	*0.062*	385/1826
P2			0.109*	*0.061*	0.110*	*0.066*	
P3			0.127*	*0.065*	0.129*	*0.069*	
Women							
P1	0.018	*0.023*	0.134**	*0.059*	0.116*	*0.064*	372/1873
P2			0.153**	*0.065*	0.135**	*0.069*	
P3			0.171**	*0.070*	0.153**	*0.073*	

Interpretation: ****: significant at the 1% level, **: significant at the 5% level, *: significant at the 10% level.*

Reading: *the first two columns show the results for the baseline differences between treated and non-treated, the next two the ones for the different follow-ups periods (P_i), and the two last the difference between these two differences (i.e. the difference between treated and non-treated at follow-up, minus the difference between treated and non-treated at baseline). Results are shown for men and women, physical and psychosocial treatments and matched and unmatched differences.*

Field: *Population aged 20-74 in 2006. Sixth iteration: 14 years of mono-exposure / 7 years of poly -exposure thresholds, 21-year observation period, 7 years minimum at work.*

Source: *Sip (2006).*

Table VIII: Results of the Difference in Differences models (i9)

Treatment /Gender	Baseline (first difference)		Follow-up (first difference)		Diff-in-Diff		N (Treat./Tot.)
	Diff.	Std. error	Diff.	Std. error	Diff.	Std. error	
UNMATCHED SAMPLE: Physical treatment							
Men							
P1	-0.038**	*0.016*	-0.029	*0.045*	0.009	*0.048*	589/1858
P2			-0.011	*0.047*	0.026	*0.050*	
P3			-0.033	*0.050*	0.005	*0.052*	
Women							
P1	-0.025	*0.021*	0.153**	*0.072*	0.178**	*0.075*	343/1785
P2			0.144*	*0.076*	0.169**	*0.079*	
P3			0.150*	*0.080*	0.174**	*0.083*	
MATCHED SAMPLE: Physical treatment							
Men							
P1	-0.029	*0.019*	0.021	*0.050*	0.050	*0.053*	570/1668
P2			0.046	*0.052*	0.075	*0.055*	
P3			0.035	*0.054*	0.064	*0.057*	
Women							
P1	-0.006	*0.024*	0.157**	*0.078*	0.163**	*0.081*	329/1568
P2			0.151*	*0.082*	0.157*	*0.085*	
P3			0.165*	*0.086*	0.171*	*0.089*	
UNMATCHED SAMPLE: Psychosocial treatment							
Men							
P1	0.001	*0.021*	0.121*	*0.068*	0.119*	*0.071*	264/1858
P2			0.160**	*0.071*	0.159**	*0.074*	
P3			0.171**	*0.073*	0.170**	*0.076*	
Women							
P1	0.017	*0.026*	0.308***	*0.083*	0.291***	*0.087*	263/1785
P2			0.325***	*0.087*	0.308***	*0.091*	
P3			0.333***	*0.089*	0.316***	*0.093*	
MATCHED SAMPLE: Psychosocial treatment							
Men							
P1	0.002	*0.022*	0.130*	*0.073*	0.128*	*0.077*	250/1638
P2			0.172**	*0.075*	0.170**	*0.078*	
P3			0.186**	*0.078*	0.184**	*0.081*	
Women							
P1	0.004	*0.031*	0.264***	*0.089*	0.260***	*0.094*	250/1327
P2			0.258***	*0.093*	0.253**	*0.099*	
P3			0.282***	*0.097*	0.278***	*0.102*	

Interpretation: ****: significant at the 1% level, **: significant at the 5% level, *: significant at the 10% level.*
Reading: *the first two columns show the results for the baseline differences between treated and non-treated, the next two the ones for the different follow-ups periods (P_i), and the two last the difference between these two differences (i.e. the difference between treated and non-treated at follow-up, minus the difference between treated and non-treated at baseline). Results are shown for men and women, physical and psychosocial treatments and matched and unmatched differences.*
Field: *Population aged 20-74 in 2006. Ninth iteration: 20 years of mono-exposure / 10 years of poly -exposure thresholds, 25-year observation period, 10 years minimum at work.*
Source: *Sip (2006).*

5.2. Description of the main results

Generally speaking our results show that, after taking care of both unobserved individual and temporal heterogeneities using a difference in differences framework as well as the selection process in the labour market with a matching method, the exposure to detrimental working conditions seems to impact individuals' declarations of chronic diseases, on a short to mid run. We present the main results of matched difference in differences according to several criteria such as gender, type of exposure, length of exposure and time horizon related to the treatment's date (P_1, P_2 and P_3).

Our results show that women's declaration of chronic diseases tend to be more affected than men's by the exposure to detrimental working conditions. In our samples, treated women declare a significant increase of their chronic diseases early on when exposed to psychosocial working conditions while it is the case for treated men only in the 3 last iterations (from i6 to i9). Psychosocially treated women declare a mean number of chronic diseases starting at a statistically significant difference of 0.09 and 0.140 chronic disease more for the treated population on the fourth iteration at P_1 and P_3 periods (*i.e.* after only 10 years of exposures to one detrimental psychosocial working condition and/or 5 years to multiple of them). This goes from 0.116 on P_1 to 0.153 on P_3 for the sixth iteration (*i.e.* for 14 years of single exposure and/or 7 years of poly-exposure). When reaching the ninth iteration (20 years of mono-exposure and/or 10 years of poly exposure), the difference on the means of chronic diseases between treated and non-treated women goes up to 0.260 in P_1 and to 0.278 in P_3. In men, the first sensible difference between treated and non-treated happens later, and is slightly less important: from 0.103 in P_1 to 0.129 in P_3 for the sixth iteration, and from 0.128 (P_1) to 0.184 (P_3) in the ninth iteration.

On the other hand, the exposure to physical working conditions does not seem to impact women's health status early, but does starting from the sixth iteration: from 0.104 mean number of chronic disease more within two years for P_1 to 0.123 for P_3. The three last iterations confirm these results, with a difference between treated and non-treated going up to 0.163 to 0.171 for i9. Our physical treatment does not seem to impact men, at any time nor iteration in our samples.

The impact of the exposure to detrimental working conditions on the declaration of chronic diseases seems, as expected and seen in the literature, to depend a lot on the duration and nature of exposures. It is also a matter of gender and time after the exposure: even though we did not check the significance of the differences between P_1 and P_3 at this stage, it seems the effect of the exposure gets bigger in time. The matching method tends, in women, to help in assessing an effect of detrimental physical working conditions on chronic diseases while tempering the effect of psychosocial working conditions. In men, it does not seem to add much in terms of impacts on chronic diseases.

6. Discussion

In this study, we were able to highlight different results. First, it appeared that our physically treated population was in better initial health status than our non-treated population (this does not hold for psychosocial treatment). This result goes in line with the notion of endogeneous sorting, inducing that people with better health status will be more numerous to chose a work with more difficult physical working conditions (and better payout) than people in worse health status. This difference is decreasing over periods of time, after the treatment occurred. Our main results using (matched) Difference in differences methods and taking into account for the time, simultaneity and intensity of exposure indicates that, despite the fact that non-treated start their career with a worse health condition than treated, exposed men and women report significantly more chronic diseases on following periods. In men, the effect of exposure to detrimental physical working conditions does not seem to increase the number of chronic diseases within the 6 years following the treatment but the exposure to years of psychosocial strains does. In women, the impact is more widespread, as the exposure to physical working conditions impacts their declaration of chronic diseases on the long run, when psychosocial strains do so starting very early on.

Another contribution of this paper is its attempt to take into account the endogeneity biases of working conditions in relation to health coming from endogeneous sorting and unobserved heterogeneity, considerations still quite uncommon in the literature. We also take into account potentially time-shifted health effects as our indicator of chronic diseases covers the entire lifespan of individuals, since their childhood.

However, several factors should be examined further, and questions remain (some of them will be worked on later, as shown in the frame below). Regarding our treatment variable and iteration thresholds, robustness checks, particularly with regard to years thresholds from which individuals are considered treated will be performed. We make use of several matching variables, accounting for the entry year on the labor market, education, gender and childhood main events. There might be some other interesting variables to consider (even though the *curse of dimensionality* does not allow us the use of too many variables).

There is an obvious declaration/memory bias in this retrospective study: some of our individuals are pretty old at the date of the survey, and their own declarations may therefore be less precise, or even biased due to different conceptions of the same facts, according to generations. Even if it is impossible to deal completely with such a bias, we matched our population according to their entry year on the labour market (*i.e.* their generation) and their level of education (shown as one of the deciding factor when it comes to memory biases), so that in the end we compare individuals with potentially the same kind of declaration/memory bias.

We use a wide definition of chronic diseases (the one used by the Sip survey). This definition is not the same as the official, administrative one (which is way more precise). While this does not allow us to make direct comparisons, it helps reducing the declaration bias induced by complicated notions (such as the official definition): our data are self-declared and our individuals are from different generations. The use of a wide, easy to understand concept such as Sip's definition of chronic diseases helps in having more homogeneity in their declaration. Yet, it would be interesting to know more about what chronic diseases are reported by our individuals.

To the attention of the discussant.

Here is a (non-comprehensive) list of what we plan to do in the near future (from most important to least). Your help and advice on these points is very welcome!

- Doing all our models on the same sample (same sample for every iteration).
- Handling the possibility of the exposure to detrimental working conditions after the treatment occurred (using a variable in the difference in differences that accounts for the intensity of post-treatment exposure).
- We chose to only keep the individuals who declared having “always” faced a detrimental working condition. We need to test that, including those who “often” did as well: it would make more sense considering how the questions are designed (notably, there might be a specific declaration bias making people reluctant to answer something as absolute as “always” and prefer more mitigate options instead) + the non-significance of our physical treatment may induce a badly designed treatment (we compare people having always faced this strain for that long to people having faced it often or less, for that long or less).
- Robustness check for the common trend assumption (we already have a good idea of this point thanks to the matching method which reduced baseline individual heterogeneity of the declaration of chronic diseases). Yet, it would be nice to have a specific test on that.
- Robustness check using panel models in the difference-in-differences (supposed to give very comparable results).

And to go further:

- Adding time-varying controls in the difference in differences, like smoking habits, handicaps and accidents.
- We want to create a third treatment, taking into account all 10 of our working conditions indicators at once, in order to take care of possible non-independence of the indicators.
- We also would like to test the long run effects of the exposure to detrimental working conditions, using our largest samples (first iterations), and adding more chronic diseases periods, to see if those effects end-up decreasing over time.

7. Conclusion

This study shows that difficult working conditions faced during the professional career of individuals impact workers’ health status, by an increased declaration of chronic diseases. These effects, *a priori* expunged from endogeneity biases coming from endogeneous sorting on the labor market according to the initial health capital are stronger for women, but still significantly impact men’s health status. These results therefore highlight two interesting facts in terms of public policy: the most affected workers in terms of health status are women, although by far the least exposed to these working conditions, and the effect of exposure is potentially still strong on the long run. Targeted policies should therefore be put in place to better take into account these two facts.

8. Acknowledgements

The authors wish to thank Pierre Blanchard (Upec Érudite) and Emmanuel Duguet (Upec Érudite) for their technical help. They also wish to thank Yann Videau (Upec Érudite), Patrick Domingues (Upec Érudite) and François Legendre (Upec Érudite) for their useful advice during the conception of this study.

9. References

Askenazy P, Caroli E. 2006. Innovative work practices, information technologies and working conditions: evidence for France, *IZA Working Paper* n°2321.

Bahu M, Coutrot T, Mermillod C, Rouxel C. 2012. Appréhender les interactions entre la santé et la vie professionnelle et leur éventuel décalage temporel, premier bilan d'une enquête innovante : SIP, Document de travail, *Série sources et méthodes*, n°35.

Barnay T. (2015) "Health, Work and Working Conditions: A Review of the European Economic Literature", *European Journal of Health Economics*, First Online, DOI: 10.1007/s10198-015-0715-8. Blackwell M, Iacus S, King G, Porro G. 2010. Cem: Coarsened Exact Matching.

Blanchet D, Debrand T. 2007. Souhaiter prendre sa retraite le plus tôt possible: santé, satisfaction au travail et facteurs monétaires. *Economie et statistique*, *403*(1), 39-62.

Bildt C, Michélsen H. 2002. Gender differences in the effects from working conditions on mental health: a 4-year follow-up. *International archives of occupational and environmental health*, *75*(4), 252-258.

Bué J, Coutrot T, Guignon N, Sandret N. 2008. Les facteurs de risques psychosociaux au travail. *Revue française des affaires sociales*, (2), 45-70.

Charbotel B, Croidieu S, Vohito M, Guerin AC, Renaud L, Jaussaud J, Bergeret A. 2009. Working conditions in call-centers, the impact on employee health: a transversal study. Part II. *International archives of occupational and environmental health*, *82*(6), 747-756.

Cohidon C, Santin G, Imbernon E, Goldberg M. 2010. Working conditions and depressive symptoms in the 2003 decennial health survey: the role of the occupational category. *Social psychiatry and psychiatric epidemiology*, *45*(12), 1135-1147.

Cottini E, Lucifora C. 2013. *Inequalities at work Job quality, Health and Low pay in European Workplaces*. GINI Discussion Paper 86.

Debrand T, Lengagne, P. 2008. Working conditions and health of European older workers. *WP IRDES N8*.

Devaux M., Jusot F., Sermet C., Tubeuf S. (2008) : « Hétérogénéité sociale de déclaration de l'état de santé et mesure des inégalités de santé », RFAS N°1, pp. 29-47.

Fletcher JM, Sindelar JL, Yamaguchi, S. 2011. Cumulative effects of job characteristics on health. *Health economics*, *20*(5), 553-570.

Givord P. 2010. Méthodes économétriques pour l'évaluation des politiques publiques. *Insee*, document de travail, G2010/08.

Hammer TH, Saksvik PØ, Nytrø K, Torvatn H, Bayazit M. 2004. Expanding the psychosocial work environment: workplace norms and work-family conflict as correlates of stress and health. *Journal of Occupational Health Psychology*, *9*(1), 83.

Harrington JM. 2001. Health effects of shift work and extended hours of work. *Occupational and Environmental medicine*, *58*(1), 68-72.

Iacus SM, King G and Porro G. 2008. Matching for Causal Inference Without Balance Checking.

Johnson JV, Hall EM, Theorell T. 1989. Combined effects of job strain and social isolation on cardiovascular disease morbidity and mortality in a random sample of the Swedish male working population. *Scandinavian journal of work, environment & health*, 271-279.

Kaikkonen R, Rahkonen O, Lallukka T, Lahelma E. 2009. Physical and psychosocial working conditions as explanations for occupational class inequalities in self-rated health. *The European Journal of Public Health*, ckp095.

Karasek RA. 1979. Job demands, job decision latitude, and mental strain: Implications for job redesign. *Administrative science quarterly*, 285-308.

Laaksonen M, Rahkonen O, Martikainen P, Lahelma E. 2006. Associations of psychosocial working conditions with self-rated general health and mental health among municipal employees. *International archives of occupational and environmental health*, *79*(3), 205-212.

Pisljar T, van der Lippe T, den Dulk L. 2011. Health among hospital employees in Europe: A cross-national study of the impact of work stress and work control. *Social science & medicine*, *72*(6), 899-906.

Robone S, Jones AM, Rice N. 2011. Contractual conditions, working conditions and their impact on health and well-being. *The European Journal of Health Economics*, *12*(5), 429-444.

Santin G, Cohidon C, Goldberg M, Imbernon E. 2009. Depressive symptoms and atypical jobs in France, from the 2003 Decennial health survey. *American journal of industrial medicine*, *52*(10), 799-810.

Shmueli A. (2003): "Socio-economic and demographic variation in health and in its measures: the issue of reporting heterogeneity", Social Science and Medicine, 57:125–134.

Siegrist J. 1996. Adverse health effects of high-effort/low-reward conditions.*Journal of occupational health psychology*, *1*(1), 27.

Theorell T, Karasek RA. 1996. Current issues relating to psychosocial job strain and cardiovascular disease research. *Journal of occupational health psychology*, *1*(1), 9.