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Harder, better, faster... yet stronger?
Working conditions and self-declaration of chronic diseases

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Abstract: The role of working conditions on workers' health status has been widely acknowledged in the literature in general but has received less attention in economics, due to the inherent statistical biases and the lack of data available to determine the role of simultaneous and chronic exposures. This study aims at estimating the causal impact of detrimental working conditions on the self-declaration of chronic diseases in France. Using a rebuilt retrospective lifelong panel and defining indicators for physical and psychosocial strains, we implement a mixed econometric strategy relying on difference-in-differences and matching methods taking into account for selection biases as well as unobserved heterogeneity. For men and women, we find deleterious effects of both types of working conditions on the declaration of chronic diseases after exposure, with varying patterns of impacts according to the strains' nature and magnitude. These results bring insights on the debate linked to legal age retirement postponement and plead for policies happening early in individuals' careers in order to prevent subsequent, mid-career health repercussions as well as schemes more focused on psychosocial risk factors.

Key words: Working conditions; Chronic diseases; Difference-in-differences; Matching

JEL classifications: J81; I14; C32

INTRODUCTION

In a context of changing and increasing work pressures (Askenazy and Caroli, 2010), the question of working conditions has become even more acute. Notably, a law implemented in 2015 in France, fits into this logic and offers access to training programs in order to change job, or the opportunity to retire earlier for the most exposed workers.

The relationship between employment, work and health status has received considerable attention in the scientific community, especially in fields such as epidemiology, sociology, management, psychology or ergonomics. In economics and on a theoretical standpoint, the differences in wages between equally productive individuals can be explained by differences in the difficulty of work-related tasks, meaning workers with poorer working conditions are paid more than others in a perfectly competitive environment (Rosen, 1974). In this framework, it is possible to imagine that health capital and wealth stock are substitutable, hence workers using their health in exchange for income (Muurinen and Le Grand, 1985). From an empirical point of view, in a general context of legal retirement age postponement linked to the increase in life expectancy and the need to maintain the financial equilibrium of the pension system, the question of working conditions and their potential effects on health status becomes crucial. Prolonged exposures during the whole career are indeed likely to prevent the most vulnerable from reaching further retirement ages, *a fortiori* in good health condition. However this research area benefited from less attention because of important endogeneity problems such as reverse causality, endogenous selection and unobserved heterogeneity (Barnay, 2016) as well as the difficulty to fully embrace the diversity and magnitude of exposures. Nevertheless, for a huge majority, studies agree on a deleterious effect of detrimental working conditions on health status.

In this paper, we examine the role of physical and psychosocial working conditions on the declaration of chronic diseases. We extend on the aforementioned literature by two means. We work on a sample of around 6,700 French male and female workers coming from the Health and Professional Route French survey (*Santé et Itinéraire Professionnel* – Sip) for whom we are able to reconstruct their entire career from their entry on the labour market to the date of the survey, using retrospective panel data. This allows us to take care of the inherent endogeneity in the relationship caused by selection biases and unobserved heterogeneity using difference-in-differences methodology combined with matching methods. We are also able to establish and analyze the role of progressive and differentiated types of exposures and account for potentially delayed effects on health status. We believe such a work does not exist in the literature, and provides useful insights for policy-making about the importance of considering potentially varying degrees of exposures and both physical and psychosocial risk factors in a career-long perspective.

The paper first presents an overview of the economic literature (Section 1), then the data (Section 2) and empirical methodology (Section 3). Finally, we present and discuss the results (Sections 4 and 5).

1. Literature

1.1. Global effect of work strains on health status

Unlike in fields such as epidemiology, working conditions and their impact on health status did not receive a lot of attention in the economic literature (Barnay, 2016; Fletcher *et al.*, 2011). Yet, this literature agrees on a deleterious mean effect of work strains on workers' health capital. The numerous existing indicators used to assess this role usually classifies into two main categories: strains related to physical or environmental burdens (expected to influence mostly physical health status) and psychosocial risk factors (supposed to have a major part in the deterioration of mental health).

Having a physically demanding job is known to impact self-rated health (Debrand and Lengagne, 2008). Notably, Case and Deaton (2003) use multiple cross-sectional data and find that manual work significantly deteriorates self-assessed health status. This result is robust to the inclusion of classical socio-demographic characteristics such as education and varies according to the levels of pay and skills involved, lower-skilled and paid workers indeed suffering greater damage on their health than higher-skilled, better paid ones. This has been later confirmed by Choo and Denny (2006), also on cross-sectional data, controlling for chronic diseases and risky health behaviours. Using panel data, Ose (2005) finds that, after taking into account possible compensations, a heavy workload causes ill health and greater absenteeism. Also on panel data, Robone *et al.* (2011) focus on the role of the workplace, atypical work hours (including night work) and job satisfaction in general and find that working conditions influence both self-assessed health and well-being. Job satisfaction is confirmed having a positive effect on objective and subjective health status measures on panel data (Fischer and Sousa-Poza, 2009). Just like physical load, work environment is found to have an influence on workers' health status. In a study on U.S. workers, the impact of having detrimental environmental working conditions (weather, extreme temperatures or moisture) specifically impacts young worker’s self-rated health status (Fletcher *et al.*, 2011). This result, obtained on panel data using random effects ordered probits, accounts for initial health status. Datta Gupta and Kristensen (2008) show, using longitudinal data and cross-country comparisons, that a favourable work environment and a high job security lead to better health conditions, after controlling for unobserved heterogeneity.

Psychosocial risk factors have been studied more recently in the empirical literature (Askenazy and Caroli, 2010), even though their initial formulation in the psychological field is older (Karasek, 1979; Theorell and Karasek, 1996). Individuals in a situation of *Job strain* (*i.e.* exposed to high job demands and low decisional latitude) are found to suffer from coronary heart disease more frequently (Kuper and Marmot, 2003). Johnson *et al.* (1989) demonstrated that social isolation, simultaneous to *Job-strain*, was correlated with cardiovascular diseases (*Iso-strain* situation). Mental health is also potentially impaired by such exposures. Based on this psychosocial literature, Laaksonen *et al.* (2006) show that stress at work, job demands, weak decision latitude, the lack of justice and support are related to poorer health status. Bildt and Michélsen (2002) show that being exposed to various work stressors, such as weak social support, lack of pride at work and general job demands, may be related to a worse mental health condition when Cohidon *et al.* (2010) stress the role of being in contact with the public. Improving on this ground, part of the literature focuses on the role of rewards at work and how it might help coping with demanding jobs (Siegrist, 1996). Notably, de Jonge *et al.* (2000) use the Effort-Reward Imbalance model on a large-scale cross-sectional dataset and find effects of Job demands and control model and Effort-Reward Imbalance model on workers’ well-being. Cottini and Lucifora in 2013 use three waves of European data (waves 1995, 2000, 2005) on 15 countries. They take into account the endogeneity of working conditions related to selection on the labour market based on initial health status and find that job quality (in particular job demands) affects mental health.

1.2. The role of simultaneous and chronic exposures

Even though the economic literature on the topic of simultaneous exposures (multiple exposures at once) or cumulative exposures (length of exposure to given strains) to detrimental working conditions is scarce, other fields such as epidemiology demonstrated their importance in the study of the impact of working conditions on health status (Michie and Williams, 2003). The literature focusing on Karasek’s and Siegrist’s models studies the results of combined exposures to several work stressors at once (see for instance the concepts of *Job-strain* and *Iso-strain*). de Jonge *et al.* (2000) show independent and cumulative effects of both types of models. On the matter of cumulative exposures, Amick *et al.* (1998) demonstrate on longitudinal data that cumulative exposures to low job control is related to higher mortality in women. The study of Fletcher *et al.* (2011) uses panel data and analyses the role of physical and environmental cumulative exposures on a time span of five years (from 1993 to 1997), while controlling for initial health status and health-related selection. This study is likely to be the closest paper in the literature to the present study. They aggregate several working conditions indicators and create composite scores, which they then sum over five years. They find clear impacts of these indicators, in both men and women, with variations depending on demographic subgroups. The biggest weakness of the paper may rely on the 5-year period of possible exposures, which is rather short. It is indeed possible to imagine larger effects in case of longer exposures, following similar trends over time. They also do not provide evidence for psychosocial risk factors.

1.3. Biases

The assessment of the health-related consequences of exposures to working conditions in the literature is, however, more often than not plagued with several methodological biases leading to potentially misleading results. First, the choice of a job is unlikely a random experience (Cottini and Lucifora, 2013), resulting in contradictory assumptions. In particular, healthier individuals may tend to prefer (self-selection) or to be preferred (discrimination) for more demanding jobs (Barnay *et al.*, 2015). In this case, the estimations are likely to be biased downwards because of healthier individuals exposed to demanding jobs being overrepresented in the sample (inducing a *Healthy Worker Effect* – Haan and Myck, 2009). On the other hand, the assumption according to which workers with lesser health capital may benefit from fewer opportunities on the labour market and thus be restricted to the toughest jobs is also reasonable, leading in that case to an upward bias. Then, unobserved individual and temporal heterogeneities unaccounted for may also result in biased estimations (Lindeboom and Kerkhofs, 2009). Individual preferences, risk aversion behaviours but also shocks, crises or other time-related events can render doubtful the hypothesis of exogeneity of working conditions (Bassanini and Caroli, 2015).

Because of the lack of panel data including detailed information for both work and health status on longer periods, few papers really succeeded in handling these biases. Notably, Cottini and Lucifora (2013) implemented an instrumental variable strategy on repeated cross-sectional data 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 difficulty to find accurate and reliable instruments for working conditions, the question of selection and unobserved heterogeneity is either treated differently or eluded altogether when working in cross-section. In contrast, Fletcher *et al.* (2011) used panel data, lagged health status indicators and random effects frameworks to handle both endogenous sorting and unobserved heterogeneity.

2. 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[1] and Labour[2]. The panel is composed of two waves: one in 2006 and one in 2010, both being conducted on roughly the same sample of individuals aged 19-74 in 2006 and with the same questions[3]. Two questionnaires are proposed: the first one is

[1] *Directorate for Research, Studies, Assessment and Statistics (Drees) – Ministry of Health.*
[2] *Directorate for Research, Studies and Statistics (Dares) – Ministry of Labour.*
[3] *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.*

administered directly by an interviewer and investigates individual characteristics, health and employment statuses. It also contains a lifegrid allowing the reconstruction of a biography of individuals' life: childhood, education, health, career and working conditions as well as major life events. The second one is self-administered and focuses on more sensitive elements such as health-related risky behaviours (weight, alcohol and tobacco consumption). Overall, more than 13,000 individuals are interviewed in 2006 and 11,000 of them in 2010 as well, making this panel survey representative of the French population[4].

We make specific use of the biographic dimension of the 2006 survey by reconstructing workers' career and health events yearly[5]. We are therefore able to know, for each individual, his/her employment status, working conditions and chronic diseases every year from their childhood to the date of the survey (2006). As far as work strains are concerned, the survey provides information about ten indicators of exposure: night work, repetitive work, physical load and exposure to toxic materials, 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 diseases for which the onset and end dates are available.

In this study, we are working on this reconstructed longitudinal retrospective dataset, composed of more than 6,700 individuals with their career and health-related data available from their childhood to the year of the survey. Thus, the final sample we are working on is composed of around 3,500 men and 3,200 women, for whom we have complete information of and who respects our inclusion criteria (see 5.4.).

3. Empirical analysis

3.1. Econometric strategy

3.1.1. Difference-in-differences general framework

A difference-in-differences methodology handles heterogeneity coming from individual and temporal unobserved characteristics: the choice of a job depends on a lot of unobserved characteristics, such as individual preferences, risk aversion behaviours, elements related to initial health capital as well as conjuncture effects. These elements, being unaccounted for, are likely to be linked to individuals' health status as well as exposures in terms of working conditions (endogenous sorting on the labour market), hence representing several serious endogeneity sources in our study. This situation can be described, using the following model:

$$y_{i,t} = \alpha T_i + \gamma_G + \delta_t + \mu_{i,t} \tag{1}$$

where $y_{i,t}$ is the outcome and $\mu_{i,t}$ the error term both depending on individual i and time t and T_i represents the treatment. The method consists in two main objectives. It tackles unobserved time-invariant group heterogeneity (γ_G) as well as temporal group-invariant (δ_t) heterogeneity between treated (T) and controls (C) using panel data on two periods: one before the treatment (t) and one after the treatment ($t+1$).

$$\begin{gathered}\left(y_{i,t+1}^T - y_{i,t+1}^C\right) - \left(y_{i,t}^T - y_{i,t}^C\right) = \\ \alpha T_i + \left[\left(\gamma_G^T - \gamma_G^C\right) - \left(\gamma_G^T - \gamma_G^C\right)\right] + \left[\left(\delta_{t+1}^T - \delta_{t+1}^C\right) - \left(\delta_t^T - \delta_t^C\right)\right] + \left[\left(\mu_{i,t+1}^T - \mu_{i,t+1}^C\right) - \left(\mu_{i,t}^T - \mu_{i,t}^C\right)\right]\end{gathered} \tag{2}$$

[4] *For a technical note on attrition management and data calibration in the Sip survey, see De Riccardis (2012).*
[5] *It is not possible to know what happened between 2006 and 2010, making the latter wave unusable in this study.*

The validity of this framework is based on the Conditional Independence Assumption (CIA), stating that outcomes of the treated and control populations would have been the same if the former would not have been treated (*i.e.* $y_i \perp T, C | \, T_i = 0$). If this (rather strong) assumption is not verified as is (which is likely to be the case when the two groups do not share similar characteristics), the estimations are at risk to be biased, formally inducing:

$$\left(\delta_{t+1}^{T} - \delta_{t+1}^{C}\right) - \left(\delta_{t}^{T} - \delta_{t}^{C}\right) \neq 0 \quad (3)$$

Even though the determination of the two groups (treated and control) can be realized *ad hoc*, it is possible (or even important, considering the assumption previously mentioned) to wisely build them (Givord, 2008), so that the differences existing between the two populations in terms of observable characteristics (and therefore health status) are reduced *ex-ante* as much as possible. This can be done, notably by using specific pre-treatment characteristics (X_i) and matching methods prior to the difference-in-differences, so that the CIA assumption may hold conditionally to these observables (*i.e.* $y_i \perp T, C | \, X_i, T_i = 0$).

3.1.2. Matching method

To create more homogeneity between treated and control groups *ex-ante* and to deal with health-related selection biases on the labour market, we perform a matching method prior to the difference-in-differences setup. We implement a Coarsened Exact Matching method (CEM – Blackwell *et al.*, 2010). The main objective of this methodology is to allow the reduction of both univariate and global imbalances between the treated and the control groups according to several pre-treatment covariates (Iacus *et al.*, 2008). CEM divides continuous variables into different subgroups based on common empirical support and can also regroup categorical variables into fewer, empirically coherent items. It then creates strata based on individuals (treated or controls) achieving the same covariate values and match them accordingly by assigning them weights[6] (unmatched individuals are weighted 0). It offers two main advantages compared to other matching methods. It helps coping effectively with the *curse of dimensionality* by preserving sample sizes: coarsening variables in their areas of common empirical support ensures a decent number of possible counterfactuals for each treated observation in a given stratum, 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.*, 2008). Yet, this 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.

3.1.3. Estimation in our study

Practically, we perform the matched difference-in-differences by simple weighted linear regressions using the Ordinary Least Squares estimator of the following model, explaining the mean number of chronic diseases (y_i):

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

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 control group, 1 for the treated), $Period_i \times T_i$ (variable of interest) is the cross variable including periods and treatment and β_1, β_2 and β_3

[6] *The weight value for matched individuals equals* $\frac{n_S^T}{n_S^C} \times \frac{N^C}{N^T}$, *with* n_s *representing the sample size for respectively the treated (T) and control (C) groups in stratum s and N the total sample sizes for both groups.*

are their respective coefficients. The error term is denoted ε_i. The estimation of this model is weighted, according to the results of the prior matching method.

3.2. Variables of interest

3.2.1. Working conditions: definition of a treatment

We use ten individual annual indicators to assess the exposure to detrimental work strains and regroup them into two relevant categories. The first one represents the physical load of work and includes night work, repetitive work, physical load and exposure to toxic materials. The second one forms the psychosocial risk factors, with 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 declare if they “Always”, “Often”, “Sometimes” or “Never” faced it during this period: we consider one individual to be exposed if he/she “Always” or “Often” declared facing said work strain. In order to take into account for the cumulative effects between strains, we consider two types of exposure: single exposure (when the individual faced only one strain at a time each year) and poly exposure (if the individual faced two or more strains simultaneously each year). Then, the duration of exposure is accounted for by introducing varying minimum durations of exposure (thresholds).

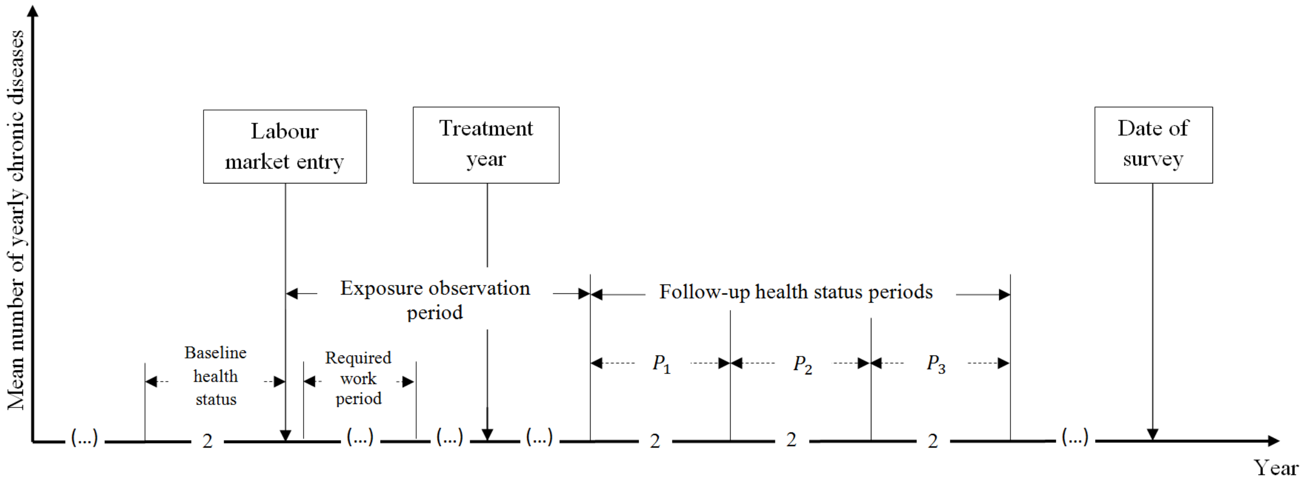
To allow for more homogeneity in terms of exposure and treatment dates and to ensure that exposure years cannot be too spread up, we observe the exposure to working conditions within a dedicated period (starting from labour market entry year). In order to be a treated, one must reach the treatment threshold within this observation period (the other ones are considered controls). Finally, minimum durations of work are introduced: individuals not participating to the labour market are likely to be too specific in terms of labour market and health characteristics, hence not really comparable to other workers (Llena-Nozal *et al.*, 2004).

3.2.2. Chronic diseases

The indicator of health status is the annual number of chronic diseases[7]: 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 broader than the administrative definition, and is self-declarative. This indicator is available from childhood to the date of the survey (2006). Available chronic diseases include cardiovascular diseases, cancers, pulmonary problems, ENT disorders, digestive, mouth and teeth, bones and joints, endocrine and metabolic and ocular problems, nervous and mental illnesses, neurological problems, skin diseases and addictions. Figure 1 explains the general framework used in this study.

[7] *Only accidents, handicaps and chronic diseases can be reconstructed year by year in the Sip survey, and to avoid mixing-up too different types of indicators we chose to keep only the latter.*

Figure 1: Working conditions and chronic diseases periods setup



Source: *Author.*

Four chronic diseases periods are defined. The baseline period consists in the two years before labour market entry and represents an indicator for initial, exogenous health capital. After labour market entry, employment and working conditions are observed and the treatment may happen (this period also includes minimum requirements in terms of labour force participation). Following this observation period are three subsequent, two-year chronic diseases follow-up periods (P_1 to P_3), indicating short to mid-term post-treatment health status.

3.2.3. Matching variables and controls

Matching pre-treatment variables are chosen so that they are relevant in terms of health status and determination in the labour market, as well as helping to cope with the (self-)selection biases. Individuals are matched according to their entry year on the labour market (in order to get rid of temporal heterogeneity related to generation/conjuncture effects); their gender (as described by Devaux *et al.* in 2008 and Shmueli in 2003, men and women do not have the same declarative patterns when it comes to health and labour market outcomes); their education level (four levels: no education, primary or secondary, equivalent to bachelor degree and superior); their health status before labour market entry (heavy health problems and handicaps) to have a better assessment of their initial health status and to cope with endogenous sorting on the labour market; and important events happening during childhood, aggregated into two dummy variables (on the one hand, heavy health problems of relatives, death of a relative, separation from one or more parent and on the other hand violence suffered from relatives and violence at school or in the neighbourhood) as it is pretty clear that such childhood events may impact early outcomes in terms of health status (Case *et al.*, 2005; Lindeboom *et al.*, 2002).

After reaching the treatment, workers can still be exposed to varying levels of working conditions. This possibility of post-treatment exposures is accounted for by a control variable in the difference-in-differences models (taking value 0 at baseline and respectively 1, 2 or 3 depending if the individual has hardly been exposed, a little or a lot to detrimental work strains during this period).

3.3. Thresholds determination process

In order to assess the role of varying degrees of exposure on health status, nine progressive exposure levels (iterations) are designed, in order to assess potentially varying effects on the declaration of chronic diseases. However, changing the treatment thresholds will, as a consequence, lead to other necessary changes in the parameters, notably the duration of the working conditions observation period and the minimum duration at work within it. The exposure thresholds range from 4 years of single exposure or 2 years of poly exposure (i_1) to respectively 20 and 10 years (i_9) of exposure, with a step of 2 years (*resp.* 1 year) from an iteration to another for single (*resp.* poly) exposures (see Appendix 1).

4. Results

4.1. Naive analysis

4.1.1. Sample description

Table 1 below gives a description of the sample used in the 7th iteration described above (the working conditions exposure threshold is defined as having been exposed to at least 16 years of single strains or 8 years to multiple, simultaneous strains). We choose this specific iteration as it should give an adequate representation of the average of the studied population (as it is the middle point between presented iterations i_5 to i_9[8] and because it should not differ on other characteristics for the most part, as the samples used for all iterations are the same). First five columns give the general sample means, standard errors, minimums, maximums and size for each considered variables. The six following columns, separated in two categories according to the treatment type, give the means on four subsamples (treated or control groups for each category).

The main conclusions of these descriptive statistics are first that the future physically treated population seem to be in better initial health condition than the control group. Such a difference cannot be found in the psychosocial sample. On the other hand, no significant effect of the physical treatment is observed on subsequent numbers of chronic diseases. This is once again the contrary for the psychosocial subsample which displays growingly significant and negative differences in the number of chronic diseases between treated and controls, revealing a potentially detrimental effect of psychosocial exposures on health status. However, the structure of the treated and control groups being very heterogeneous in terms of observed characteristics, the chronic diseases differences for each period between the two are likely to be unreliable. Yet, there seem to be, at least for physically demanding jobs, signs of a sizeable selection effect pointing out that healthier individuals prefer or are preferred for this type of occupations.

[8] *Only iterations i_5 to i_9 are presented for space saving because previous iterations reveal no significant effect of the exposure to detrimental working conditions on chronic diseases.*

Table 1: Base sample description (i_7)

Variable	Mean	Std. error	Min	Max	N	Physical sample			Psychosocial sample		
						Treated	Control	Diff.	Treated	Control	Diff.
Treatment											
Physical treatment	.47	*.50*	0	1	1667	-	-	-	-	-	-
Psychosocial treatment	.44	*.50*	0	1	1538	-	-	-	-	-	-
Health status											
Initial chronic diseases	.12	*.36*	0	4.67	3527	.10	.13	.04***	.12	.11	-.01
Follow-up chronic diseases (P_1)	.63	*.93*	0	9.50	3527	.65	.62	-.03	.70	.58	-.12***
Follow-up chronic diseases (P_2)	.72	*.99*	0	9.00	3527	.73	.70	-.03	.80	.65	-.15***
Follow-up chronic diseases (P_3)	.82	*1.07*	0	9.00	3527	.83	.82	-.02	.91	.76	-.15***
Demography											
Entry year on the labour market	1963	*8.65*	1941	1977	3527	1962	1965	2.65***	1963	1963	0.37
Men	.51	*.50*	0	1	1811	.63	.41	-.21***	.54	.49	-.05***
Women	.49	*.50*	0	1	1716	.37	.59	.21***	.46	.51	.05***
Age	59.67	*7.67*	42	74	3527	60.20	59.20	-.99***	59.94	59.47	-.47*
No diploma	.13	*.33*	0	1	445	.18	.08	-.09***	.14	.11	-.03**
Inf. education	.62	*.48*	0	1	2200	.69	.57	-.12***	.61	.64	.03*
Diploma equivalent to bachelor	.12	*.32*	0	1	410	.07	.16	.09***	.11	.12	.01
Sup. education	.12	*.32*	0	1	411	.05	.18	.13***	.12	.12	.00
Childhood											
Problems with relatives	.44	*.50*	0	1	1538	.47	.40	-.07***	.48	.41	-.07***
Violence	.09	*.29*	0	1	316	.10	.08	-.02**	.12	.07	-.05***
Severe health problems	.13	*.33*	0	1	450	.13	.12	-.01	.14	.12	-.02*
Physical post-exposure											
None	.57	*.49*	0	1	2021	.26	.85	.59***	.48	.65	.17***
Low	.20	*.40*	0	1	699	.30	.11	-.20***	.22	.18	-.04***
High	.23	*.42*	0	1	807	.44	.04	-.39***	.30	.17	-.13***
Psycho. post-exposure											
None	.57	*.49*	0	1	2024	.48	.66	.18***	.27	.81	.53***
Low	.21	*.43*	0	1	739	.25	.18	-.07***	.31	.14	-.18***
High	.22	*.41*	0	1	764	.27	.17	-.11***	.41	.06	-.35***

Interpretation:** *: difference significant at the 1% level, **: difference significant at the 5% level, *: difference significant at the 10% level. Standard errors in italics. The average number of chronic diseases in the whole sample before labour market entry is* 0.12. *In the future physically treated population, this number is* 0.10 *(which is significantly lower than in the future control group, i.e.* 0.13 *at the 1% level). Such a difference at Baseline in health statuses between future treated and control groups does not exist in the psychosocial sample.*
***Field:** Population aged 42-74 in 2006 and present from i_1 to i_9. 7th iteration. Initial, unmatched sample.*
***Source:** Health and Professional Route survey (Sip), wave 2006.*

4.1.2. Unmatched difference-in-differences results

The results for unmatched difference-in-differences naive models for the five iterations (i_5 to i_9) are presented in rows in Table 6 and 7 (Appendix 2), and can be interpreted as differences between groups and periods in the mean numbers of chronic diseases. Despite not taking into account for the possibility of endogenous selection in the sample nor differences in observable characteristics between the two groups' structures, these models do take care of unobserved, group-fixed heterogeneity. As expected after considering the sample description given in Table 1, unmatched baseline differences (*i.e.* differences in chronic diseases between treated and control populations before labour market entry) display statistically significant negative differences between future physically treated and controls in men (Table 6). These differences cannot be witnessed in women or for the psychosocial treatment (Table 7). The possibility of endogenous sorting hence cannot be excluded. The positive follow-up differences (*i.e.* differences in the numbers of chronic conditions between treated and control populations after the treatment period and not accounting for initial health status) indicate that the treated population reported higher numbers of chronic diseases than the control group in average. Logically, these differences are growing in magnitude as the exposure degree itself becomes higher.

Difference-in-differences results (*i.e.* the gap between treated and control populations, taking into account for differences in initial health status) suggest a consistent effect of detrimental work strains on the declaration of chronic conditions, which increases progressively as exposures intensify. While physical strains appear to play a role on the declaration of chronic diseases straight from i_5 in both men and women, effects after psychosocial strains seem to require higher levels of exposure to become statistically significant: in men, first significant differences appear from i_6 (i_7 in women). These effects do not turn out to be short term only, as the differences tend to grow bigger when considering later periods of time.

4.2. Main results

4.2.1. Matching

These naive results tend to confirm the possibility of a (self-)selection bias in the sample, inducing 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. In order to minimize this selection process, a matching method is used prior to the difference-in-differences models.

Table 2 gives a description of the same sample used in i_7 presented earlier (for comparison purposes), after matching using CEM. The matching method succeeds in reducing the structural observed heterogeneity between the treated and control groups for every single pre-treatment covariate. Heterogeneity still exists, namely for the entry year on the labour market and age, but is shown as minor and in any case non-significant (difference of less than a month in terms of labour market entry year and of approximately a quarter for age). It is also interesting to note that initial health status differences are also greatly reduced, and that bigger negative Follow-up differences between treated and controls can now be observed, making the hypothesis of a detrimental impact of working conditions on health status more credible.

Table 2: Matched sample description (i_7)

Variable	Physical sample			Psychosocial sample		
	Treated	**Control**	**Diff.**	**Treated**	**Control**	**Diff.**
Health status						
Initial chronic diseases	.08	.10	.02	.10	.10	-.00
Follow-up chronic diseases (P_1)	.63	.55	-.07**	.68	.54	-.13***
Follow-up chronic diseases (P_2)	.72	.63	-.09***	.78	.62	-.16***
Follow-up chronic diseases (P_3)	.82	.72	-.10***	.89	.72	-.17***
Demography						
Entry year on the labour market	1962	1962	.08	1963	1963	-.01
Men	.63	.63	0	.54	.54	0
Women	.37	.37	0	.46	.46	0
Age	60.02	60.31	.28	59.82	59.61	-.21
No diploma	.15	.15	0	.13	.13	0
Inf. education	.72	.72	0	.65	.65	0
Diploma equivalent to bachelor	.06	.06	0	.10	.10	0
Sup. education	.05	.05	0	.11	.11	0
Childhood						
Problems with relatives	.45	.45	0	.46	.46	0
Violence	.07	.07	0	.07	.07	0
Severe health problems	.10	.10	0	.10	.10	0

Interpretation: ****: difference significant at the 1% level, **: difference significant at the 5% level, *: difference significant at the 10% level. After matching, there is no significant difference between the future treated and control groups in terms of initial mean number of chronic diseases, for both physical and psychosocial samples.*
Field: *Population aged 42-74 in 2006 and present from i_1 to i_9. 7th iteration. Matched (weighted) sample.*
Source: *Health and Professional Route survey (Sip), wave 2006.*

4.2.2. Matched difference-in-differences

The results for matched difference-in-differences models for the five iterations are available in Table 3 and Table 4 below. These results, relying on matched samples, take care of the selection biases generated by endogenous sorting on the labour market and observed heterogeneity, as well as unobserved group-fixed and time-varying heterogeneities as a result of the use of difference-in-differences frameworks.

Table 3: Matched difference-in-differences results (i_5 to i_9), physical treatment

Treatment	Baseline		Follow-up		Diff.-in-Diff.		N	% matched
Gender	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error	(treat./tot.)	(treat./contr.)
Men (i_5)								
P_1			.047	*.066*	.071	*.069*		
P_2	-.024	*.020*	.048	*.069*	.072	*.072*	1928/3242	
P_3			.059	*.050*	.083	*.054*		90% / 88%
Women (i_5)								
P_1			.090	*.058*	.104*	*.061*		
P_2	-.014	*.019*	.091*	*.051*	.105*	*.055*	1228/3048	
P_3			.102*	*.056*	.116**	*.059*		
Men (i_6)								
P_1			.036	*.072*	.058	*.074*		
P_2	-.022	*.019*	.040	*.076*	.062	*.078*	1908/3226	
P_3			.044	*.074*	.066	*.076*		90% / 88%
Women (i_6)								
P_1			.141**	*.060*	.155**	*.063*		
P_2	-.014	*.020*	.149***	*.055*	.163***	*.059*	1164/3040	
P_3			.162**	*.067*	.177**	*.070*		
Men (i_7)								
P_1			.041	*.075*	.064	*.077*		
P_2	-.023	*.017*	.053	*.076*	.077	*.078*	1908/3258	
P_3			.086	*.078*	.110	*.080*		91% / 88%
Women (i_7)								
P_1			.190***	*.068*	.197***	*.071*		
P_2	-.007	*.018*	.204***	*.073*	.212***	*.076*	1130/3046	
P_3			.208**	*.081*	.215***	*.083*		
Men (i_8)								
P_1			.095	*.069*	.107	*.071*		
P_2	-.013	*.017*	.118*	*.070*	.131*	*.072*	1838/3256	
P_3			.121	*.076*	.134*	*.078*		92% / 87%
Women (i_8)								
P_1			.211**	*.083*	.211**	*.085*		
P_2	-.000	*.019*	.229***	*.078*	.229***	*.080*	1066/3026	
P_3			.242***	*.072*	.243***	*.075*		
Men (i_9)								
P_1			.116*	*.064*	.123*	*.066*		
P_2	-.007	*.016*	.149**	*.066*	.156**	*.068*	1712/3264	
P_3			.152**	*.070*	.159**	*.072*		92% / 86%
Women (i_9)								
P_1			.249***	*.081*	.252***	*.083*		
P_2	-.003	*.019*	.241***	*.086*	.244***	*.089*	972/2980	
P_3			.267***	*.075*	.270***	*.077*		

Interpretation: ****: significant at the 1% level, **: significant at the 5% level, *: significant at the 10% level. Standard errors in italics. The Baseline and Follow-up columns show the results for the first differences between the treated and control groups respectively before and after the treatment. The Diff.-in-diff. column shows the results for the second differences (i.e. the difference between Follow-up and Baseline differences). The last column denotes the percentage of the initial sample that found a match, respectively for the treated and control groups.*
Field: *Population aged 42-74 in 2006 and present from i_1 to i_9. Matched (weighted) sample.*
Source: *Health and Professional Route survey (Sip), wave 2006.*

Table 4: Matched difference-in-differences results (i_5 to i_9), psychosocial treatment

Treatment Gender	Baseline Coefficient	Baseline Std. Error	Follow-up Coefficient	Follow-up Std. Error	Diff.-in-Diff. Coefficient	Diff.-in-Diff. Std. Error	N (treat./tot.)	% matched (treat./contr.)
Men (i_5)								
P_1			.029	*.039*	.015	*.042*		
P_2	.014	*.016*	.042	*.041*	.028	*.044*	1578/3350	
P_3			.041	*.045*	.027	*.048*		89% / 93%
Women (i_5)								
P_1			.042	*.056*	.044	*.061*		
P_2	-.003	*.024*	.058	*.054*	.061	*.059*	1358/3072	
P_3			.069	*.053*	.072	*.058*		
Men (i_6)								
P_1			.082*	*.043*	.073	*.046*		
P_2	.009	*.016*	.084*	*.046*	.074	*.048*	1552/3320	
P_3			.138***	*.047*	.128***	*.049*		90% / 91%
Women (i_6)								
P_1			.051	*.058*	.063	*.063*		
P_2	-.012	*.024*	.070	*.053*	.082	*.059*	1414/3076	
P_3			.071	*.062*	.083	*.066*		
Men (i_7)								
P_1			.122**	*.049*	.117**	*.051*		
P_2	.005	*.016*	.132**	*.056*	.127**	*.059*	1496/3320	
P_3			.151**	*.066*	.145**	*.068*		90% / 93%
Women (i_7)								
P_1			.165***	*.059*	.170***	*.063*		
P_2	-.005	*.023*	.171**	*.072*	.175**	*.076*	1276/3146	
P_3			.181***	*.065*	.186***	*.068*		
Men (i_8)								
P_1			.136**	*.067*	.123*	*.069*		
P_2	.012	*.017*	.140***	*.050*	.128**	*.053*	1426/3322	
P_3			.173**	*.069*	.160**	*.071*		91% / 92%
Women (i_8)								
P_1			.197**	*.081*	.199**	*.084*		
P_2	-.002	*.023*	.222***	*.072*	.224***	*.076*	1196/3110	
P_3			.235***	*.065*	.237***	*.069*		
Men (i_9)								
P_1			.142**	*.073*	.131*	*.075*		
P_2	.011	*.017*	.145***	*.053*	.134**	*.055*	1290/3304	
P_3			.169**	*.074*	.158**	*.076*		91% / 91%
Women (i_9)								
P_1			.220***	*.081*	.223***	*.084*		
P_2	-.003	*.023*	.238***	*.072*	.241***	*.075*	1114/3102	
P_3			.245***	*.066*	.248***	*.070*		

Interpretation: ****: significant at the 1% level, **: significant at the 5% level, *: significant at the 10% level. Standard errors in italics. The Baseline and Follow-up columns show the results for the first differences between the treated and control groups respectively before and after the treatment. The Diff.-in-diff. column shows the results for the second differences (i.e. the difference between Follow-up and Baseline differences). The last column denotes the percentage of the initial sample that found a match, respectively for the treated and control groups.*
Field: *Population aged 42-74 in 2006 and present from i_1 to i_9. Matched (weighted) sample.*
Source: *Health and Professional Route survey (Sip), wave 2006.*

Even though these matched results do not hold on the exact same samples as the naive models presented in Tables 6 and 7 and therefore do not allow for direct comparisons, it is to be noted that around 90% of the initial sample is preserved after matching. The intuitions given in Table 2 seem to be confirmed by the Baseline (first two columns) and Follow-up (next two columns) differences presented in Table 3 and Table 4, indicating that matching the samples on our pre-treatment variables systematically succeeds in reducing initial health status gaps between treated and control groups, to a point where none of them are still present in the matched results.

First, it appears clearly that men are much more exposed to detrimental working conditions than women, especially for physically demanding jobs (with an average of 20 percentage points (pp) more in men than in women), but also to a lesser extent for psychosocial risk factors (+3pp in men). Before giving an analysis of the results, it is to be noted that the exposures characterized here are exposures happening within the first part of the professional career: as explained in Table 5, depending on the iteration considered, the working conditions observation periods go from the first 18 years (i_5) to the first 30 years (i_9) after labour market entry. This basically means that these workers were exposed at the beginning of their career, when they were relatively young (and quite possibly more resilient to work strains). As is, the results presented below essentially depict the role of early-career exposures on subsequent numbers of chronic diseases.

Taking into account for differences in health status before labour market entry, observed characteristics, selection biases as well as unobserved group or time-dependant heterogeneities, a clear impact of the exposure to work strains on the declaration of chronic diseases can be observed in the difference-in-differences (columns 5 and 6). Treated workers indeed seem to suffer from a much quicker degradation trend in their health status than their respective control groups. This trend exists between levels of exposure (iterations) but is also suggested by the evolution of the number of chronic diseases by period (P_1 to P_3), even though these gaps are unlikely to be significant. This main result holds for both treatment types and for both genders and tend to demonstrate possible long term effects of exposures rather than short term-only consequences.

In the physical sample, the first significant consequences in terms of health status degradation can be seen in women, starting from i_5 (*i.e.* after respectively 12 years of single exposure or 6 years of simultaneous exposures), while this is the case much later in men, at i_8 (*resp.* after at least 18 or 9 years of exposure). Between i_5 and i_9, the differences between treated and controls in the mean number of chronic diseases in women is multiplied by a factor of around 2.7 (from $.104$ to $.270$) while in men, the growth factor is less than 1.21 between i_8 and i_9 (from $.131$ to $.159$). Psychosocial strains have a more homogenous starting impact on the declaration of chronic diseases, with sizeable health status consequences happening at i_7 (*resp.* 16 or 8 years of exposure) for both men and women. The difference in means in women (*resp.* in men) is 1.46 (1.35) times bigger at i_9 compared to i_7, going from $.170$ to $.248$ (*resp.* from $.117$ to $.158$ in men). Thus, even though women are less exposed than men to work strains, it seems that their health status is more impacted by them.

5. Discussion and conclusion

In this study, we are able to highlight links between physical or psychosocial working conditions and chronic diseases in exposed male and female, on French retrospective panel data. Workers facing gradually increasing strains in terms of duration or simultaneity of exposure are more frequently coping with raising numbers of chronic diseases. Using combined difference-in-differences and matching methods, our empirical strategy helps to handle both (self-)selection on the labour market based on health status and other observable characteristics as well as unobserved group and temporal heterogeneity. Based on a career-long temporal horizon both for exposures and health status observation periods, we find major differences in terms of health condition between treated and control groups that are very likely the result of past exposures to work strains. To our knowledge, this is the first paper to work on both simultaneous and cumulative effects of two distinct types of work strains with such a large horizon, while acknowledging the inherent biases related to working conditions.

However, the paper suffers from three main limitations. Working on retrospective panel data and on long periods of time, our estimations are at risk to suffer from declaration biases. Our individuals are rather old at the date of the survey, and their own declarations in terms of working and health conditions are therefore likely to be less precise (recall biases) or even biased (*a posteriori* justification or different conceptions according to different generations). Even if it is impossible to deal completely with such a bias, matching on entry year on the labour market (*i.e.* their generation) and on education (one of the deciding factors when it comes to memory biases) should help in reducing recall heterogeneity. Also, simple occupational information, notably, tends to be recalled rather accurately, even on longer periods (Berney and Blane, 1997). Regarding our treatment variable, there is no interaction allowed between the two types of work strains (physical and psychosocial). The empirical framework we rely on does not allow for multiple simultaneous treatments, so the only possibility would be the design of a third type of treatment, combining all ten strains indicators. Yet this third, overall treatment would not be comparable to the other two. Also because of the method we use and the sample sizes we are working with, it is not possible to analyze clearly the potential heterogeneity in the effect of working conditions on health status across demographic and socio-economic categories, even though this mean effect is shown to vary (Fletcher *et al.*, 2011; Muurinen and Le Grand, 1985). Finally, we use a wide definition of chronic conditions as our indicator for health status. This indicator does not allow for direct comparisons with the literature (commonly used indicators such as self-assessed health status or activity limitations are not available on a yearly basis) and the retained definition in the Sip survey differs from the French administrative one. Yet we believe that, because it is less specific than the official definition of chronic conditions, it may represent a good proxy of general health status while at the same time being less subject to volatility in declarations compared to self-assessed health (*i.e.* more consistent).

These results plead for more preventive measures happening early in individuals' careers. As it appears, major health degradations (represented by the onset of chronic conditions) tend to follow exposures happening as soon as the first half of the career. These preventive measures may first focus workers on physically demanding jobs while also targeting workers facing psychosocial risk factors, the latter still being very uncommon in public policies notably in France. These targeted schemes may benefit both to the society in general (by higher levels of general well-being at work and reduced healthcare expenditures later in life) and firms (more productive workers and less sick leaves). It notably appears that postponing the legal age of retirement must be backed-up by such preventive measures in order to avoid detrimental adverse health effects linked to workers being exposed longer, taking into account for both types of working conditions (which is not the case in the 2015 French pension law). Today, the human and financial costs of exposures to detrimental working conditions seem undervalued in comparison to the expected implementation cost of these preventive measures.

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APPENDIX 1: ITERATION DETERMINATION PROCESS

Table 5: Iterations description

Iteration Parameter	i_1	i_2	i_3	i_4	i_5	i_6	i_7	i_8	i_9
Treatment thresholds									
Single 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									
Working conditions observation period	6	9	12	15	18	21	24	27	30
Minimum duration at work	2	3	4	5	6	7	8	9	10

Indications: *in years.*
Reading: *for the seventh iteration (i_7), an individual must reach 16 years of single exposure or 8 years of poly exposure within the 24 years following labour market entry to be considered a treated. Also, he/she must have worked at least 8 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 periods) after the end of the working conditions observation period.*
Source: *Author.*

The nine iterations are designed according to increasing levels of exposures to detrimental working conditions: a 2-year step for single exposures from an iteration to another. Poly exposure durations are half the single ones. The durations of the working conditions observation periods is set arbitrary so that it allows some time to reach the treatment thresholds: it represents three-half the maximum duration of exposure needed to be a treated, *i.e.* three half of the single 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 length of chronic diseases observation periods is set to two years, in order to avoid choosing too specific singletons while preserving sample sizes.

We perform our estimations on these nine iterations, on the same sample of individuals: we only keep individuals existing in all nine of them for comparison purposes. The sample is thus based on the most demanding iteration, i_9. This means that, in our setup, individuals must be observed for a minimal duration of 38 years (2 years before labour market entry for baseline health status, plus 30 years of observation and 6 years of follow-up health status periods as well as a minimum of 10 years on the labour market – see Figure 1). In other words, the date of the survey being 2006, this means the retained individuals are the ones entering the labour market before 1970 (and existing in the dataset before 1968), inducing heavily reduced sample sizes in comparison to the 13,000 starting individuals.

APPENDIX 2: NAIVE UNMATCHED DIFFERENCE-IN-DIFFERENCES MODELS

Table 6: Unmatched difference-in-differences results (i_5 to i_9), physical treatment

Treatment	Baseline		Follow-up		Diff.-in-Diff.		N (treat./tot.)
Gender	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error	
Men (i_5)							
P_1			.056	*.047*	.087*	*.050*	
P_2	-.032**	*.016*	.057	*.041*	.089**	*.044*	2148/3622
P_3			.059	*.044*	.091*	*.047*	
Women (i_5)							
P_1			.073	*.047*	.096*	*.051*	
P_2	-.023	*.019*	.078	*.052*	.102*	*.055*	1358/3432
P_3			.080	*.049*	.103*	*.053*	
Men (i_6)							
P_1			.053	*.046*	.093*	*.049*	
P_2	-.040**	*.016*	.068	*.051*	.107**	*.053*	2130/3622
P_3			.069	*.048*	.108**	*.051*	
Women (i_6)							
P_1			.094*	*.054*	.116**	*.057*	
P_2	-.021	*.019*	.102**	*.050*	.124**	*.054*	1290/3432
P_3			.114*	*.059*	.135**	*.062*	
Men (i_7)							
P_1			.065	*.054*	.110**	*.056*	
P_2	-.045***	*.016*	.068	*.052*	.113**	*.054*	2086/3622
P_3			.088	*.057*	.133**	*.059*	
Women (i_7)							
P_1			.118	*.073*	.135*	*.076*	
P_2	-.016	*.019*	.136**	*.060*	.152**	*.063*	1248/3432
P_3			.144**	*.066*	.160**	*.068*	
Men (i_8)							
P_1			.105*	*.055*	.142**	*0.057*	
P_2	-.036**	*.015*	.116**	*.057*	.153***	*0.059*	1996/3622
P_3			.119*	*.062*	.155**	*0.064*	
Women (i_8)							
P_1			.122	*.076*	.133*	*0.079*	
P_2	-.011	*.020*	.168**	*.071*	.179**	*0.073*	1170/3432
P_3			.184***	*.065*	.194***	*0.068*	
Men (i_9)							
P_1			.097*	*.056*	.128**	*0.058*	
P_2	-.031**	*.015*	.114**	*.058*	.145**	*0.060*	1852/3622
P_3			.115*	*.061*	.146**	*0.063*	
Women (i_9)							
P_1			.134*	*.079*	.154*	*0.081*	
P_2	-.019	*.020*	.177**	*.073*	.197***	*0.076*	1060/2372
P_3			.194***	*.067*	.213***	*0.070*	

Interpretation: ****: significant at the 1% level, **: significant at the 5% level, *: significant at the 10% level. Standard errors in italics. The Baseline and Follow-up columns show the results for the first differences between the treated and control groups respectively before and after the treatment. The Diff.-in-diff. column shows the results for the second differences (i.e. the difference between Follow-up and Baseline differences).*
Field: *Population aged 42-74 in 2006 and present from i_1 to i_9. Unmatched sample.*
Source: *Health and Professional Route survey (Sip), wave 2006.*

Table 7: Unmatched difference-in-differences results (i_5 to i_9), psychosocial treatment

Treatment	Baseline		Follow-up		Diff.-in-Diff.		N (treat./tot.)
Gender	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error	
Men (i_5)							
P_1			.014	*.035*	.000	*.038*	
P_2	.014	*.015*	.027	*.037*	.013	*.040*	1734/3622
P_3			.028	*.040*	.014	*.042*	
Women (i_5)							
P_1			.092*	*.052*	.060	*.056*	
P_2	.032	*.020*	.099**	*.049*	.067	*.053*	1558/3432
P_3			.103**	*.048*	.071	*.051*	
Men (i_6)							
P_1			.074*	*.039*	.068	*.042*	
P_2	.006	*.015*	.082**	*.041*	.077*	*.044*	1708/3622
P_3			.134***	*.045*	.129***	*.048*	
Women (i_6)							
P_1			.096*	*.053*	.071	*.057*	
P_2	.025	*.020*	.107**	*.050*	.083	*.054*	1484/3432
P_3			.109*	*.057*	.085	*.060*	
Men (i_7)							
P_1			.105**	*.045*	.101**	*.048*	
P_2	.004	*.015*	.142***	*.047*	.138***	*.050*	1662/3622
P_3			.163***	*.050*	.159***	*.052*	
Women (i_7)							
P_1			.148**	*.069*	.121*	*.072*	
P_2	.027	*.020*	.160***	*.057*	.133**	*.061*	1414/3432
P_3			.173***	*.063*	.147**	*.066*	
Men (i_8)							
P_1			.132***	*.049*	.123**	*.051*	
P_2	.010	*.016*	.161***	*.050*	.151***	*.052*	1574/3622
P_3			.193***	*.054*	.183***	*.056*	
Women (i_8)							
P_1			.180**	*.071*	.160**	*.074*	
P_2	.020	*.020*	.209***	*.065*	.189***	*.068*	1322/3432
P_3			.222***	*.060*	.202***	*.063*	
Men (i_9)							
P_1			.131***	*.050*	.119**	*0.053*	
P_2	.011	*.016*	.164***	*.052*	.153***	*0.054*	1428/3622
P_3			.190***	*.056*	.179***	*0.058*	
Women (i_9)							
P_1			.208***	*.073*	.194**	*0.076*	
P_2	.014	*.020*	.232***	*.066*	.218***	*0.069*	1212/3432
P_3			.234***	*.062*	.219***	*0.065*	

Interpretation: ****: significant at the 1% level, **: significant at the 5% level, *: significant at the 10% level. Standard errors in italics. The Baseline and Follow-up columns show the results for the first differences between the treated and control groups respectively before and after the treatment. The Diff.-in-diff. column shows the results for the second differences (i.e. the difference between Follow-up and Baseline differences).*
Field: *Population aged 42-74 in 2006 and present from i_1 to i_9. Unmatched sample.*
Source: *Health and Professional Route survey (Sip), wave 2006.*

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