The impact of working conditions on absenteeism

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Abstract:
This paper explores how bad working conditions impact absenteeism at work through their effect on health. Our contribution is two-fold. First, we develop a model of labour supply which accounts for the evolution of health status. Second, we empirically estimate the effect of working irregular schedules on sickness absence for male manual workers. To reduce the selectivity bias, we use a propensity score matching method and test its robustness with a “selection on unobservables” specification. Our estimates show that working irregular schedules has a significant impact on sickness absence, the sign and the extent of which crucially depend on age.

Key words: working conditions; health demand; absenteeism; work schedules; matching.

JEL Classification: I12; J22; J28; J81

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Data used in this analysis are readily available to any researcher for purposes of replication.


Introduction

This paper studies the impact of working conditions on sickness absence. Whereas well-documented in epidemiological and sociological literature, this question has been neglected by economists. Yet it is of particular relevance for public policy. In an ageing society, painfulness of job may not be sustainable. In this respect improving the quality of jobs in order to raise the participation rate in Europe is a key policy objective fixed by the Lisbon Council (2000)\(^1\). Besides, the increase in the amount of sickness benefits paid by the public health insurance system constitutes a recurring source of concern for the French public authorities. A better understanding of the economic determinants of absenteeism is thus essential.

Our paper tries to estimate the issue of the impact of working conditions on sickness absence. Our contribution is two-fold. We first develop a theoretical model to illustrate how working conditions affect sickness absence through their effect on health. Our model shows that if bad working conditions are compensated even partially by pay premiums their impact on sickness absence is ambiguous. Under these conditions, the question of the impact of working conditions on sickness absence becomes an empirical question. The working conditions variable that we retain for our empirical work is related to working time arrangements and oppose employees working irregular schedules to those working (weekly) regular schedules. We restrict our sample to a relatively homogeneous population: male manual workers of the private sector.

The empirical estimates of the impact of working irregular schedules on sickness absence constitute the second contribution of this paper. To reduce the selection bias due to observed heterogeneity, we use propensity score matching methods. In order to check the robustness of our estimates, we also use a “selection on unobservables” specification.

The remaining of the paper is organized as follows. Section 1 discusses the economic literature on the subject. Section 2 presents the theoretical framework. Section 3 stresses on the empirical problems posed by the measure of working conditions and their impact on health. Section 4 gives the econometric strategy and results. Section 5 concludes.

1. Health, work and absence: a review of literature

Our study covers three domains: working conditions, health, and absenteeism. To our knowledge these three dimensions have rarely been studied within an integrated economic framework.

As underlined by Brown and Sessions (1996), little attention has been paid in the economic literature to the question of absenteeism and its causes, contrary to other disciplines of social sciences. A first trend of the literature in the 1970s was based on the neo-classical labour supply model, wherein the propensity for an employee to be absent depends on the difference between contractual and desired hours, i.e. those which maximize worker’s utility under budget constraint. The model predicts that an increase in contractual hours will increase the tendency to be absent.

A second trend, based on the shirking model of Shapiro and Stiglitz (1984), formalized the problem in terms of moral hazard, considering absence as revealing the employee’s level of effort. In this context several authors explored how to limit the effects of moral hazard. Most often the variable of interest was the replacement rate, i.e. the ratio between the wage rate and the sick-leave compensation. Meyer, Viscusi and Durbin (1995), Bolduc et alii (2002) or Adren (2005) for example confirmed the disincentive effect of low replacement rates on sickness absence.

These models combined with bargaining models provided the theoretical framework to explain the contra-cyclical fluctuations of sickness absence (i.e. absence decreases when unemployment increases): a worse situation on the labour market decreases the bargaining power of an employee and consequently decreases his propensity to claim sickness leave (i.e. increases his level of effort) for fear of being laid off. Similarly, Engellandt and Riphahn (2005) or Arai and Thoursie (2005) have documented the negative correlation between sickness absence and temporary contracts.

In their comparative study on absenteeism in twelve European countries, Frick and Malo (2005) introduced the above-mentioned determinants. They calculated national indicators characterizing for each country the degree of generosity of the wage compensation system for sickness absence, the level of unemployment and the degree of job protection. In their empirical models, the effects of these institutional variables are in conformity with what is generally found in the literature but are likely to
be less important than those produced by individual characteristics such as the existence of health-related problems on the workplace.

This very last point illustrates one of the critics formulated by Brown and Sessions (1996) against the theoretical models which generally ignore the individual’s health status even though they deal with sickness absence. Doing this, these models implicitly assume that absence never comes from the employee’s incapacity to work but reveals his choice not to work. To circumvent this limitation Barmby, Sessions and Treble (1994) enriched the theoretical framework based on moral hazard and incorporated an index of sickness as a preference parameter into the utility function. To enlarge the theoretical framework based on moral hazard, Grignon and Renaud (2004) distinguished the so-called claim reporting moral hazard, which corresponds to the “pure” ex post moral hazard, and the risk-bearing moral hazard, which may be connected with the preventive behaviour of both the employer and the employee and is the variable of interest when studying working conditions and their impacts on behaviour. On this basis their empirical work consisted in disentangling these two potential effects. For her part, Ose (2005) tried to separately identify voluntary absence on the one hand and involuntary absence for health-related problems due to bad working conditions on the other.

If up to recently absence was a subject rather neglected in the economic literature, working conditions per se received even less attention. As a matter of fact they were “absorbed” in the theory of equalizing differences (Rosen, 1974) which predicts that pecuniary and non pecuniary advantages and disadvantages of a job must be equalized. Thus activities which offer unfavourable working conditions must pay premiums as compensation. This contrasts with the literature in epidemiology or applied ergonomics, where the relation between working conditions and health or sickness absence is abundantly documented².

Anyway the existence of wage compensations does not prevent an individual from being sensitive to the non pecuniary characteristics of her job. In particular unfavourable working conditions encourage voluntary mobility (Bonhomme and Jolivet, 2005). Consequently the influence of working conditions on behaviour justifies to account for them in an economic approach. However up to this

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² See for example the numerous articles on these questions published in Social Science and Medicine or in Applied Ergonomics.
date very few papers were devoted to the role of working conditions in individual behaviour (see Askenazy and Caroli, 2003, in the French context).

To our knowledge, Case and Deaton (2005) are among the first to include simultaneously the dimensions of work and health into a theoretical model. They modeled the evolution of health status using Grossman’s model (1972), wherein an individual is supposed to invest regularly in her health capital to slow down its depreciation. They found that bad working conditions affect the rate at which health capital depreciates when the individual ages. Their empirical results showed that health declines with age more rapidly for manual workers than for non-manual workers.

2. The theoretical framework

2.1 The basic framework

We attempt to formalize the effect of working conditions on sickness absence. Our intuition is that working conditions affect absence indirectly through their impact on health status. We thus have to formalize the relation between working conditions and health.

Following Grossman (1972), health status at age \( t \) is considered as a durable good which deteriorates at rate \( \delta_t \). Individuals seek to slow down their health deterioration by investing \( i_t \) in medical care, rest and so on. The evolution of health status \( z_t \) thus follows:

\[
z_{t+1} = i_t + (1 - \delta_t)z_t
\]

We assume that \( \delta_t \) depends on environmental characteristics such as working conditions (see Sikles and Taubman, 1986). We also assume that health repair depends on absence at work \( s \) and consumption \( x \) of medical care at price \( \pi \): \( i_t = i(s_t, x_t) \), with \( i_s > 0 \) and \( i_x > 0 \).

Following Case and Deaton (2005) we make utility depend directly on health status \( z_t \) and consumption \( c_t \):

\[
u = u(c_t, z_t)
\]

with the usual assumptions: \( u_c > 0, u_z > 0, u_{cz} < 0, u_{zz} < 0 \). We also assume that \( u \) is separable in \( z_t \) and \( c_t \): \( u_{cz} = u_{zz} = 0 \).
In this context the individual chooses his level of absence by arbitrating between consumption and health. To see it, we focus on a one-period model. Let $\bar{h}$ be the contractual hours of the employee over the period considered. Let $z_0$ be his health status at the beginning of the period. According to (1), his health status at the end of the period is given by:

$$z = i(s, x) + (1 - \delta)z_0$$

(2)

The employee’s effective working time over the period is $\bar{h} - s$. Let $w$ be his wage rate and $\tau$ the compensation rate for sick leave. For sake of simplicity, we consider that the employee’s income consists only in wages and sick pay. Consequently his consumption equation is:

$$c = w(\bar{h} - s) + \tau ws - \pi x = w\bar{h} - w(1 - \tau)s - \pi x$$

(3)

An increase in $s$ will raise $z$ (according to (2)) and reduce $c$ (according to (3)). Symmetrically a decrease in $s$ will raise $c$ and reduce $z$. The optimal choice of $s$ corresponds to $\partial u(c, z)/\partial s = 0$.

By specifying the health production function as a Cobb-Douglas: $i(s, x) = \theta s^\sigma x^{1-\sigma}$, we easily show (see appendix A) that the optimal $s^*$ verifies the first-order condition:

$$[w(1 - \tau)]^{\sigma} u_s(c^*, z^*) - \kappa \sigma u_c(c^*, z^*) = 0$$

(4)

where $c^* = w\bar{h} - w(1 - \tau)s^*$, $z^* = \kappa[w(1 - \tau)]^{1-\sigma}s^* + (1 - \delta)z_0$ and $\kappa$ is a technical parameter depending on $\theta$, $\sigma$ and $\pi$.

2.2 Including working conditions into the model

Suppose that it is possible to rank jobs according to an index $p$ measuring the painfulness of work. Suppose then that working conditions have an impact on the wage rate $w$:

$$w = w(p), \text{ with } w'(p) > 0$$

(H1)

and on the health deterioration rate $\delta$:

$$\delta = \delta(p), \text{ with } \delta'(p) > 0$$

(H2)

Assumption (H1) is simply based on the remuneration schemes of the firms which are generally codified by collective agreements and consist in giving premiums to employees working in
unfavourable conditions (night duty, noisy environment,…). Assumption (H2) rests on findings duly reported in medical and ergonomic literature about the long-term negative impacts of bad working conditions on physical and mental health.

Considering \( p \) as exogenous\(^3\) and applying the implicit function theorem to (4), the optimal absence level depends on \( p : s^* = s^*(p) \). Taking then the first derivative of (4) with respect to \( p \) leads to:

\[
\frac{\partial s^*}{\partial p} = w'(p)A + \delta'(p)B
\]

where \( A \) should be negative and \( B \) positive (see appendix A for the analytical expressions of \( A \) and \( B \)). Consequently the impact of bad working conditions on sickness absence will result from two opposite effects:

- a negative effect, due to work incentive schemes based on higher remuneration ;
- a positive effect, due to the employee’s protective behaviour with respect to health depreciation.

Thus the direction of the impact is theoretically ambiguous and becomes an empirical question.

3. Measuring working conditions : an empirical problem

From an empirical point of view, studying the role of working conditions on sickness absence raises at least two difficulties. The first one is how to identify and measure working conditions. The second one concerns the availability of appropriate data.

Gollac (1997) illustrated the first point. He showed that employees’ reports on their working conditions may reflect both the reality of their work and the perception they have of it. Answers given by office workers who complained of inhaling tobacco smoke is a good example: the percentage rose from 11% in 1984 to 21% in 1991. This astonishing evolution does not reflect a workplaces degradation but the greater sensitivity of people to the presence of smokes, sensitivity reinforced by medical and public campaigns on the damaging effects of nicotinism. Similarly, Molinié (2003) tested the coherence of employees’ answers to questions about their working conditions posed at two

\(^3\) We will discuss this questionable assumption later.
successive waves of the same survey. Memory biases are significant: for example, 24% of the surveyed people who, in 1990, had stated to work or have worked in shift work, asserted five years later that they had never done it. The percentage is higher when working conditions are less objectivable: in case of carrying heavy loads, the corresponding percentage rises to 54%.

Consequently any survey which aims to measure working conditions in order to relate them to workers’ behaviour on the labour market must follow a rigorous protocol. The problem is more complex if one wishes to include health status in a causal chain connecting working conditions to observed behaviour. Generally speaking, health status is a subjective variable and thus poses problems similar to those raised by indicators of working conditions. Moreover these problems cumulate in the sense that, for example, individuals who declare themselves in bad health are induced to report their work environment as being harder than it really is. In addition the effects of working conditions on health may appear in the long term. In order to avoid memory biases like those highlighted supra, information must be collected by surveying the same individuals successively over a long period and by limiting the retrospective questionings.

To our knowledge, there does not exist any French data source which answers these requirements in a satisfactory way. The few panels available are too short or do not contain enough information both on working conditions and other characteristics of the job, on health status and sickness absence. Moreover, the total compensation rate in case of sickness absence (the $\tau$ parameter of the theoretical framework - see appendix B for some information about the French system) is not available in any survey.

Our empirical work was carried out on the French “Labour Force Survey”, a quaterly rotating survey, from January 2002 to December 2004. One decisive advantage of this data source is the sample size, large enough to allow us to select an homogeneous population, i.e. the male manual workers in private sector, aged from 18 to 59. The final sample size is 11 538.

The survey provides very detailed information on individual and job characteristics. Our working conditions variable captures working time arrangements. We oppose employees working regular schedules (whose schedules do not vary from one week to another) to those working irregular schedules (e.g. having alternate schedules - 21.4% of the sample - or whose schedules vary from one
week to another -14.8 % of the sample). The advantage of this working conditions variable is its objectivity. The negative impact of irregular schedules on health is well-documented (e.g. Costa, 1996).

An employee is considered having been absent for illness reasons if he declared not having worked for this reason during the entire “reference week”, in general the calendar week preceding the day of the interview. Thus we do not consider sickness absence of less than one week. With this measure, the absence rate is very low, which could influence the robustness of the estimates. We then use information from the second interview taking place three months later. In short our indicator of sickness absence measures absence during the whole current reference week, or/and during the whole reference week of the next quarter. It thus captures, even very partially, the delayed impact of working conditions on health. The drawback is that we have to restrict the sample to those who answered twice and were still employed at the second time\(^4\): selection bias could occur if excluded and selected individuals had different observed and unobserved characteristics. We will return to this point below.

On average, the rate of sickness absence is 5.8 %.

Table 1 gives descriptive statistics of the sample. The wages of employees working irregular schedules are on average 11 % higher than those working regular schedules. Workers aged 50 or over are more frequently working regular schedules. Irregular schedules are more present in industrial and large firms and in firms where exist flexible working time arrangements over the year.

\[\text{Table 1 around here}\]

4. Econometric strategy and results

Among male manual workers working irregular schedules, 6.2% were absent for illness reason during at least one of the two “reference” weeks. This rate varies from 3.6 % for workers aged 18-29 years to 8.4% for 50-59 years old workers (Table 2).

\(^4\) 16% of the initial sample (13 656 manual workers entering the survey from January 2002 to December 2004) was deleted.
A simple comparison of absence rates between employees working irregular and regular schedules ("naive" estimator in Table 2) exhibits a positive but not significant effect of working irregular schedules on sickness absence. The average estimate is 0.7 point.

This naive estimator is likely to be biased as employees working irregular schedules could be selected according to characteristics also related to sickness absence. For example, if workers in irregular schedules are younger than average, then ignoring the differences in age may underestimate the impact of working irregular schedules on sickness absence, as health usually declines with age. Conversely as irregular schedules are more frequent in industrial firms where workplace hazards are also more important, naive estimation will result in spurious correlation between working irregular schedules and being absent for sickness reason.

To reduce this potential bias, we use propensity-score matching (PSM) methods.

4.1. Propensity Score Matching (PSM)

The general principle of matching methods can be quickly summarized as follows (for a comprehensive presentation, see Smith and Todd, 2005). Let $I$ be the “treatment variable”. Matching consists in (a) pairing each employee who works irregular schedules ($I = 1$) with one (or more) employee(s) working regular schedules ($I = 0$) and having the same (or roughly the same) observable characteristics, (b) comparing their respective propensities to be absent.

More precisely, let $S_1$ (resp. $S_0$) be the propensity to be absent conditional on working irregular (resp. regular) schedules. For each person, only one of the two outcomes $S_0$ and $S_1$ is observed. We are interested in estimating the average effect of working irregular schedules on sickness absence, for employees working irregular schedules (Average Treatment Effect on the Treated) :

$$
\Delta = E(S_1 - S_0 \mid I = 1)
$$

The difficulty arises from the fact that we observe here only $S_1$ but not $S_0$. To circumvent this difficulty PSM methods rely on the so-called “unconfoudness assumption”. It states that the outcome $S_0$ is independent of the type of schedules $I$, conditional on a set of observables $X$ :

$$
S_0 \perp I \mid X
$$

As shown by Rosenbaum and Rubin (1983), if (6) holds then the following holds :
\[ S_0 \perp I \mid b(X) \quad (7) \]

for any “balancing” function of \( X, b(X) \), i.e. such as:

\[ X \perp I \mid b(X). \]

In particular, the “propensity score” \( p(X) = \Pr(I = 1 \mid X) \) is a balancing function of \( X \). PSM methods consists in matching on this propensity score. They eliminate bias due to observable heterogeneity by balancing the observed covariates between the treatment group (irregular schedules) and the control group (regular schedules). In practice, the propensity score is unknown and must be estimated. We follow the usual practice and estimate \( p(X) \) by using a standard logit model.

Unconfoundness is a strong assumption, and the choice of appropriate conditioning variables is critical. Our set of variables includes jobs characteristics which are likely to be linked simultaneously to different schedules and to the rate of sickness absence: branch of industry, occupation, firms’ size or type of contract (permanent or temporary). It also contains personal characteristics as age and qualification, which are closely related to health status.

We used tests on “balancing property” as specification tests for the logit function\(^5\). Remember that the balancing property is a necessary condition for assumption (7) to be satisfied.

Lastly, in order to deal with heterogeneous effects related to age, we also carried out estimation separately for workers aged 18-29, 30-39, 40-49 and 50-59 years.

Having common support for the treated and non treated is crucial when assessing the quality of the PSM method. It ensures that each employee working irregular schedules can be matched with an employee working regular schedules very similar to him. Figure 1 shows that if the two categories are clearly distinct (the modes of the two distributions are distant), their common support is wide.

\[ \text{[Figure 1 around here]} \]

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Several matching methods are possible. None of them are preferable per se. We favoured kernel matching estimators proposed by Heckman et alii (1998), which in our case give theoretically more precise estimates.\(^6\)

The difference in probability of sickness absence estimated by PSM rises now to 1.16 points and is significant at the 5% level (table 2, column (2)). Working irregular schedules thus plays a substantial part in absenteeism, as it explains 18% of total sickness absence of the concerned employees.

\[
\text{[Table 2 around here]}
\]

Estimates by age show two facts. First, the heterogeneity bias is strong. The difference between the “naive” estimator and the matching estimator is particularly impressive for the oldest group of workers. Second, the impact of irregular schedules on sickness absence is not necessarily positive, in accordance with the theoretical ambiguity. It is even negative (-0.98 points) for young people, although the difference is not significant. Finally, the difference in the rate of sickness absence between employees working irregular schedules and those working regular schedules increases with age. Beyond 40 years, it is about twice as large as the rate estimated on the whole population. Working irregular schedules explains more than one quarter of the sickness absence rate of the elderly. This stresses the need for a real dynamic model in order to study the life-cycle evolution of health status.

The PSM methods crucially depend on identifying assumption (6). It implies that we are able to observe all variables \(X\) that jointly determine the propensity to work irregular schedules and the probability of being absent for illness reason. This assumption may not hold, as unobservable heterogeneity (initial health in particular) probably remains. To evaluate the sensitivity of our results to this problem, we use an alternative empirical method. We estimated a “selection on unobservables” model, which explicitly takes into account the possible existence of unobserved characteristics jointly related to type of schedules and sickness absence.

\(^6\) Others matching methods yield similar results.
4.2. Selection on unobservables

The model consists in two equations:

\[
\begin{align*}
\text{irreg\_schedule}^* &= x_1 \beta_1 + u_1 \\
\text{sick\_absence}^* &= x_2 \beta_2 + \gamma \text{irreg\_schedule} + u_2
\end{align*}
\]

where \( \text{irreg\_schedule}^* \) and \( \text{sick\_absence}^* \) are latent variables, observed by dummies standing respectively for working irregular schedules and being absent, \( x_1 \) and \( x_2 \) are covariates and \( \beta_1 \) and \( \beta_2 \) their corresponding parameters, \( \gamma \) the parameter of interest and \( u_1 \) and \( u_2 \) residuals. If unobserved characteristics are correlated with the propensity to be absent and the type of schedules, then \( u_1 \) and \( u_2 \) are correlated.

In order (8) to be non parametrically identified, at least one variable in \( x_1 \) must be excluded from \( x_2 \). However, under distributional assumptions on residuals, this condition is not imperative. Without an exclusion variable the identification of the parameters rests on the nonlinearity of the model. We prefer to adopt this strategy, as we are unable to choose a valid exclusion variable in our data\(^7\).

With this model, the equivalent of (5) can then be written as follows. For each individual working irregular schedules, we calculate \( \tilde{\Delta} \):

\[
\tilde{\Delta} = \text{Prob}(\text{absence} = 1 \mid \text{hor\_irreg} = 1) - \text{Prob}(\text{absence} = 1 \mid \text{hor\_irreg} = 0)
\]

We then take the empirical mean of \( \tilde{\Delta} \) over the sample of employees working irregular schedules. Under the assumption that \( (u_1, u_2) \) has a bivariate standard normal distribution with correlation \( \rho \), \( \tilde{\Delta} \) equals to:

\[
\tilde{\Delta} = \frac{\Phi_2(x\hat{\beta}_1, x\hat{\beta}_2 + \hat{\gamma}, \hat{\rho})}{\Phi(x\hat{\beta}_1)} - \frac{\Phi_2(-x\hat{\beta}_1, x\hat{\beta}_2, -\hat{\rho})}{\Phi(-x\hat{\beta}_1)}
\]

\(^7\) The presence of a flexible working time agreement, closely related to irregular schedule but (apparently) not to sickness absence, could be a possible exclusion variable. Results are identical with or without it.
where $\Phi$ (resp. $\Phi_2$) is the cumulative function of the univariate (resp. bivariate) standard normal distribution, and $\hat{\beta}_1$, $\hat{\beta}_2$, $\hat{\gamma}$ and $\hat{\rho}$ the estimated parameters.

The results are given in column (3) of table 2. The bivariate probit and the PSM estimates are generally quite close. This reinforces the validity of our PSM estimates in removing (a large part of) the potential bias. However, estimates of the parameters of interest in the probit model are highly imprecise\(^8\).

5. Concluding remarks and discussion

In this paper, we proposed a theoretical model for work absenteeism, based on the assumption that bad working conditions have an indirect impact on absenteeism through the individual’s health status. This impact turns out to be theoretically ambiguous as it results from two opposite effects: a desincentive wage-effect and an incentive health-effect. In our empirical test to disentangle these two antagonist effects we conclude to a positive significant impact of working irregular schedules on sickness absence. These results call for comments.

To begin with, it is worth noticing that we do not ignore moral hazard phenomena, even if we do not try to quantify it. Our view is that it is very difficult, if not impossible, to separately identify “pure” health-related effects and “pure” ex post moral hazard. The validity of our empirical results relies on the assumption that moral hazard determinants (in particular compensation rates) are well-balanced between employees working irregular and regular schedules. The rich set of firm and personal characteristics we used and the results of our alternative “selection on unobservables” specification give us some confidence in the validity of this assumption.

However our work has at least three caveats. First, we suppose in our theoretical framework that the index of working conditions $p$ is exogenous. On the empirical level this hypothesis states that working regular or irregular schedules is out of the control of both the employee and the employer. But employees in jobs with bad working conditions may have been self-selected on observable or unobservable characteristics. Health status is one of them. As we have no information about the

\(^8\) The estimated value of $\gamma$ (resp. $\rho$) is 0.273 (resp. -0.089), with standard error is 0.385 (resp; 0.228). Detailed results are available upon request.
employee’s health status in our data we cannot control for the potential effect, reported in the medical and epidemiological literature as the “healthy worker effect”. This effect states that employees facing bad working conditions would be in better health than the others.

The second limitation of our work is precisely that it ignores demand-side phenomena. Yet these phenomena are visible in our data: 11.0% of the employees who were absent for illness reasons at the time of the first interrogation were not any more in employment three months later. The corresponding percentage for those not having declared a sickness absence at the first interrogation is 3.4%. There is obviously a link between sickness absence and end of the job contract.

This last point highlights the third caveat of our study, that is its static framework. It does not capture the dynamic effects of bad working conditions on the employee’s health status, which affect her productivity and therefore her probability to continue working.

Nevertheless our first results seem to be promising. Our theoretical approach gives us a useful framework for fruitful extensions. Concerning empirical results, the above-mentioned limitations (such as omitted health status) would tend to underestimate the impact of bad working conditions on absenteeism. We thus claim that working conditions explain a substantial part of work absence. As the public cost of sickness absence raises more and more concerns in public debate, our results suggest that this issue deserves more attention from economists than it usually receives. They also stress the necessity of appropriate data for further empirical investigations in this field.
Appendix A. The theoretical model

The employee’s health status at the end of the period is:

\[ z = \theta s^\sigma x^{1-\sigma} + (1-\delta)z_0 \]  
(A1)

The consumption equation over the period is:

\[ c = w\bar{h} - w(1-\tau)s - \pi x \]  
(A2)

The choice variables are \( s \) and \( x \). The first-order conditions are thus:

\[ \frac{\partial}{\partial s} u(c, z) = 0 \text{ and } \frac{\partial}{\partial x} u(c, z) = 0 \]  
(A3)

Inserting (A1) and (A2) into (A3), we have:

\[
\begin{align*}
\frac{\partial}{\partial s} u(w\bar{h} - w(1-\tau)s - \pi x, \theta s^\sigma x^{1-\sigma} + (1-\delta)z_0) &= 0 \\
\frac{\partial}{\partial x} u(w\bar{h} - w(1-\tau)s - \pi x, \theta s^\sigma x^{1-\sigma} + (1-\delta)z_0) &= 0
\end{align*}
\]

that is:

\[
\begin{align*}
\omega(1-\tau)u_c(c, z) &= \theta s^\sigma x^{1-\sigma}u_z(c, z) \\
\pi u_c(c, z) &= \theta(1-\sigma) s^\sigma x^{-\sigma}u_z(c, z)
\end{align*}
\]  
(A4)

Resolving (A4) gives optimal \( s^* \) and \( x^* \). Dividing each side of the first equation by the corresponding side of the second equation leads to:

\[ \frac{x^*}{s^*} = w(1-\tau)\frac{1-\sigma}{\pi\sigma} \]  
(A5)

Let \( \kappa = \theta \left(\frac{1-\sigma}{\pi\sigma}\right)^{1-\sigma} \). Using (A5), the first equation of (A4) can be rewritten as:

\[ [w(1-\tau)]^\sigma u_c(c^*, z^*) = \kappa \sigma u_z(c^*, z^*) \]  
(A6)

with:

\[
\begin{align*}
c^* &= w\bar{h} - w\left(\frac{1-\tau}{\sigma}\right)s^* \\
z^* &= \kappa [w(1-\tau)]^{1-\sigma} s^* + (1-\delta)z_0
\end{align*}
\]
We include working conditions into the model and let depend \( w \) and \( \delta \) on \( p \) (index measuring the painfulness of work), with \( w'(p) > 0 \) and \( \delta'(p) > 0 \). Let us consider \( p \) as exogenous, that is as a parameter of the model. According to the implicit function theorem, \( s^* \) depends on \( p \). Taking the first derivative of (A6) with respect to \( p \), we have:

\[
\frac{\partial s^*}{\partial p} = w'(p)A + \delta'(p)B
\]

with:

\[
A = \frac{\sigma w^{\alpha-1}(1-\tau)^\sigma u_c + w^{\alpha+1}(1-\tau)^\sigma c'u_{cc} - \kappa^2 \sigma(1-\sigma)w^{-\sigma}(1-\tau)^{1-\sigma} s u_{zz}}{\frac{w^{\alpha+1}(1-\tau)^{\alpha+1}}{\sigma} u_{cc} + \kappa^2 \sigma w^{-\sigma}(1-\tau)^{1-\sigma} u_{zz}}
\]

and:

\[
B = \frac{\kappa \sigma \sigma_0 u_{zz}}{\frac{w^{\alpha+1}(1-\tau)^{\alpha+1}}{\sigma} u_{cc} + \kappa^2 \sigma w^{-\sigma}(1-\tau)^{1-\sigma} u_{zz}}
\]

With the usual assumptions on the first and second derivatives of \( u \), we see that the denominator of \( A \) and \( B \) is negative. \( A \) is negative unless \( |\mu_{cc}| \) is too high (\( u \) too concave in \( c \)). \( B \) is positive. Thus the sign of \( \partial s^*/\partial p \) is ambiguous.

Note that if we consider \( h \) and \( \tau \) as (exogenous) parameters, applying the same reasoning leads to:

\[
\frac{\partial s^*}{\partial h} = w^{\alpha+1}(1-\tau)^\sigma u_{cc}
\]

and:

\[
\frac{\partial s^*}{\partial \tau} = \frac{w^{\alpha+1}(1-\tau)^\sigma}{\sigma} s u_{cc} - w^\sigma(1-\tau)^{\sigma-1} u_c .
\]

We thus recover some findings reported in the economic literature (see section 2), that the higher the contractual hours of work, the higher the propensity to be absent, and the higher the compensation rate for sick leave, the higher the propensity to be absent.
Appendix B. Wage compensation for sickness absence in France

According to the French Social Security system, an employee has to justify any absence at work for illness reasons by providing a medical certificate to his employer within 48 hours. Otherwise he can be penalized and in some cases be laid off. In case of sickness absence the job contract is simply suspended. However if prolonged or repeated absences of the employee hinder the efficiency of the production process and make necessary the replacement of the employee, the employer can lay him off.

In case of absence an employee in private sector is entitled to sickness benefits unless she has not been working enough. The sickness benefits are paid by the Social Security system from the 4th day of absence. There is thus a waiting period of 3 days. The benefits are equal to 50% of gross wages - within a limit - during the first 6 months, and to 51.49% beyond.

The benefits may be supplemented by employers under certain conditions fixed by collective agreements, for example by paying benefits during the first three days of absence. The employee’s seniority in the firm is an important parameter for the entitlement to supplementary benefits. Lastly private insurances can also pay a supplement.
References


## Table 1
### Descriptive statistics

<table>
<thead>
<tr>
<th></th>
<th>All</th>
<th>Regular Schedules</th>
<th>Irregular Schedules</th>
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</thead>
<tbody>
<tr>
<td>Wage (euros)</td>
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<td>1251.1</td>
<td>1393.6</td>
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<td>Flexible annual working time agreement</td>
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</tr>
<tr>
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<td>25.4</td>
<td>25.7</td>
</tr>
<tr>
<td>Age=[30-39]</td>
<td>30.6</td>
<td>29.9</td>
<td>31.9</td>
</tr>
<tr>
<td>Age=[40-49]</td>
<td>26.5</td>
<td>26.6</td>
<td>26.2</td>
</tr>
<tr>
<td>Age=[50-59]</td>
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<td>18.1</td>
<td>16.1</td>
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<tr>
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<td>22.9</td>
<td>37.0</td>
</tr>
<tr>
<td>Craft manual workers - highly qualified</td>
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<td>32.2</td>
<td>9.9</td>
</tr>
<tr>
<td>Drivers</td>
<td>12.8</td>
<td>10.2</td>
<td>17.2</td>
</tr>
<tr>
<td>Handling and transportation manual workers</td>
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<td>8.6</td>
<td>11.8</td>
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<tr>
<td>Factory manual workers – low qualification</td>
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<td>12.9</td>
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</table>

Table 2  
The effect of irregular schedules on the probability to be absent for sickness reason.

<table>
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<tr>
<th>Age</th>
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<th>Effect of working irregular schedules on the probability of being absent (2)</th>
<th>Effect of working irregular schedules on the probability of being absent (3)</th>
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</thead>
<tbody>
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<tr>
<td>30-39 years</td>
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<td>6.29</td>
<td>1.32</td>
<td>1.53</td>
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<tr>
<td>40-49 years</td>
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<td>50-59 years</td>
<td>2 014</td>
<td>8.38</td>
<td>-0.24</td>
<td>2.34</td>
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</table>


Standard errors in parenthesis. For column (2), standard errors are estimated by bootstrapping (50 iterations). (1) is the raw difference in sickness absence rates between employees working irregular schedules and those working regular schedules; (2) is the PSM estimator⁹ (kernel matching); (3) is the bivariate probit estimator. The set of control variables for (2) and (3) includes age, years of schooling, low vocational diploma, region of residence, type of contract, flexible working time agreement in the firm, branch of industry, size of the firm, occupation.

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Fig. 1. Distribution of the propensity score.

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⁹ For estimation we use the Stata procedure proposed by Becker and Ichino (2002).