Working Paper Series
Department of Economics
University of Verona

Who should monitor job sick leave?

Carlo Alberto Biscardo, Alessandro Bucciol, Paolo Pertile

WP Number: 18 April 2015

ISSN: 2036-2919 (paper), 2036-4679 (online)

WHO SHOULD MONITOR JOB SICK LEAVE?[*]

Carlo Alberto Biscardo[†], Alessandro Bucciol[‡], Paolo Pertile[§]

April 13 2015

Abstract

We use a large and unique administrative dataset from Italy, covering the period 2009-2014, to investigate opportunistic behavior (moral hazard) and the effectiveness of monitoring policies related to insurance against illness-related income losses. The analysis is based on the outcome of mandatory medical visits aimed at verifying the health status of employees during sickness spells. We find that employers are more effective than the public insurer in selecting sickness episodes to monitor. However, a reduction in the number and a better targeting of visits with the support of appropriate statistical tools may close the gap. We discuss the impact of using direct measures of health, such as the outcome of a medical visit, on the study of the determinants of opportunistic behavior and argue that simply looking at days of work lost, without appropriately controlling for health status, may lead to misleading conclusions if the goal is studying moral hazard.

Keywords: Sick leave insurance; moral hazard; absenteeism; work ability.

JEL classification: D03; I18

[*] We are grateful to Instituto Nazionale della Previdenza Sociale – INPS (Giovanni Martignoni and Verona medical office) for kindly providing us with anonymized administrative data. We thank Matteo Lippi Bruni and Marcella Veronesi for useful comments. The usual disclaimers apply.

[†] INPS, branch office Verona, Via Battisti 19, 37122 Verona, Italy. Email: carloalberto.biscardo@inps.it.

[‡] *Corresponding author*. University of Verona, Dept. of Economics, Via dell'Artigliere 19, 37129 Verona, Italy. Email: alessandro.bucciol@univr.it. Telephone: +39 045 842 5448.

[§] University of Verona, Dept. of Economics, Via dell'Artigliere 19, 37129 Verona, Italy. Email: paolo.pertile@univr.it.

1. Introduction

In all countries with extensive social security systems, employees benefit from some form of insurance against illness-related income losses.[1] Although full insurance of risk-averse individuals is efficient according to economic theory, its benefits must be assessed against the potential costs of asymmetry of information between the insurer and the employee (Flåm, 2004). Most countries employ some tools to ensure that absence from job is justified by employee's health status, but such mechanisms vary substantially by country. Some of these differences are due to a different structure of the insurance contract. However, most of these monitoring policies could be adapted to different contexts. Therefore, understanding what policies are most effective is extremely relevant and would probably deserve more attention than received so far in the literature.

Among the works exploring this area, Hartman et al. (2013) use data from an experiment on Swedish workers to study the impact of increasing the number of days of leave after which a medical certificate is required. The authors show that this weakening of regulation increased the length of sickness absence. Engström and Johansson (2012) analyze the results of an experiment conducted in Sweden, where the Swedish Social Insurance Agency sent a letter to a sample of medical centers and centers for primary health care, announcing stricter monitoring on medical certificates for job sick leave. The authors report a somewhat surprising increase in sickness benefits granted following visits in the medical centers that received the announcement.

A common assumption in virtually all the empirical literature on job sick leave is that more absenteeism is the result of more moral hazard, i.e., a larger number of employees not working even if their health would allow so. This is not surprising, given that absence from job is much easier to observe than the true health status of the employee for the researcher, as well as for the insurer. However, using absence from job to proxy for moral hazard may be too rough, at least when the focus is on the efficiency of the insurance mechanism. One reason for this is that some employees may decide to work even when this is not efficient, given their health status. This phenomenon is called "presenteeism", and is gaining increasing attention in this literature (Chatterji and Tilley, 2002; Dew et al., 2005; Johns, 2010; Pauly et al., 2008). If presenteeism is an issue, then the (change in) the

[1] According to Heymann et al. (2009), the USA is the only industrialized country with no general insurance for employees of work-unrelated sickness. Insurance is provided at the local level in six States. This raised a debate, which is still lively, on the opportunity to introduce insurance at the Federal level.

number of days not worked may be a biased measure of moral hazard. For example, an increase in the number of days worked may be the result of fewer individuals shirking among those who, given their health, should work (less shirking) or more working even though they should not (more presenteeism). Only in the first case the result can be seen as an efficiency enhancing reduction in moral hazard. Pichler and Ziebarth (2015) develop a theoretical model to disentangle the presenteeism and shirking effects on job sick leaves. Ziebarth and Karlsson (2014) try to approach the presenteeism-shirking identification issue by exploiting the correlation between insurance coverage and health state.[2] They show mixed evidence, with results suggesting that shirking prevails for some types of workers and presenteeism for others.

In principle, the only reliable way to check whether a job sick leave spell is consistent with the employee’s health condition is a medical visit to confirm, or not, inability to work. This tool is in use within the Italian social security system: sick leave monitoring is based on home visits, meant to check whether the sick leave period and the allowance associated with it – to which the worker was entitled on the basis of a general practitioner's certificate – is consistent with her health condition. At the end of the home visit, the physician can either confirm the inability to return to workplace at that time, or state the employee’s ability to return to work. The latter outcome provides a more reliable indicator of moral hazard than those commonly used in the literature, as it certifies that with no monitoring the worker would have received sick leave allowance for a number of days in excess of what her actual health state would require. In this paper, we use a large and unique administrative dataset containing information on all the home medical visits (about 90,000) undertaken in one Italian district (Verona) over the period January 2009 – December 2014. We are not aware of any other contribution to the literature using the outcome of a medical visit as a measure of potentially opportunistic behavior.

Our contribution mainly goes in two directions. First, we exploit the fact that the decision to monitor one job sick episode in Italy can be taken by either the public insurer or the private employer, to investigate whether the private firm has any informational advantage that allows to more efficiently select the episodes to monitor, as one might expect. Moreover, we do so by comparing private monitoring with three different regimes

[2] In particular, if the null hypothesis of no significant health change due to the variation in insurance coverage is rejected, this is interpreted as evidence of shirking.

of public monitoring that have been in place during the period of observation: one with a large number of visits based on a random selection mechanism, one with many visits and selection supported by a formally defined algorithm, and finally one with few visits and the formal algorithm. The algorithm makes use of observed characteristics on the worker and the illness.

Our second contribution is related to the possibility of checking whether some of the correlations on which there seems to be agreement are confirmed when a more direct measure of moral hazard is employed. Among the characteristics that received most attention in the literature there are gender (e.g., Barmby et al., 2002; Gilleskie, 2010; Herrmann and Rockoff, 2012; Ichino and Moretti, 2009), unemployment rates (e.g., Askildsen et al., 2005; Leigh, 1985; Pichler, 2014; Pfeifer, 2013), type of contract (e.g., Khan and Rehnberg, 2009; Olsson, 2009; Waehrer and Miller, 2003), and length of sickness spell (e.g., Gilleskie, 2010).

There is a handful of papers studying the relationship between some firm's characteristics, the cost of absence and absence rates. A common result is that firms where teamwork is central experience higher costs of absence (Weiss, 1985). These firms may react by adjusting contracts so that a wage premium is granted where lower absence rates are expected (Coles and Treble, 1996; Coles et al., 2007), and/or by investing more in monitoring activities (Heywood et al., 2008). Böheim and Leoni (2014) investigate the impact of a discontinuity in the proportion of cost of employees' insurance borne by the firm within the Austrian legislation. The authors do not find evidence that the different treatment implies differences in sickness absence due to different incentives for employers to invest in monitoring. However, a formal role in monitoring for the firm within a social insurance system has not been studied in any depth yet. The characteristics of the Italian insurance system, together with our original dataset, allow us to start exploring this topic, which may lead to relevant policy implications also for other countries.

Our analysis is based on a set of probit regressions, where the observation unit is the single home medical visit and the outcome of interest is ”ability to work” certified after the monitoring visit during the sickness spell. Results show that a visit is more likely to detect moral hazard when asked by the employer. Since it is the same group of physicians who make the visit, no matter whether the worker to monitor has been identified by the public insurer or the employer, this finding suggests that there is a better selection of the subset to monitor. The worker's demographic characteristics are similar in the subsets monitored by the public insurer and employers, meaning that neither is discriminating against some types of workers in comparison with the other. However, significant differences can be observed in the characteristics of the sick-leave spells monitored. Firms' greater efficiency in monitoring seems to be related to a higher probability of monitoring spells with the following characteristics, which turn out to significantly affect the probability of detecting moral hazard: length of sick-leave (negative), remaining length of sick-leave at the time of the visit (negative), and worker already monitored in the past (positive). However, we find that the combination of the two changes in the selection regime by the public insurer – the use of a formal algorithm and the cut in the number of visits conducted – greatly improved the ability of selecting workers who are "able to work". The performance achieved under the current regime is in line with that of visits requested by the employer.

Concerning our second research question, we find that the unemployment rate has a negative impact on the probability of finding an individual able to work, consistently with most of the literature on absenteeism (see, for example, Askildsen et al., 2005). The effect, however, is not robust to all specifications and we often find no correlation between unemployment rates and ability to work. Therefore, our results raise the question of whether more unemployment induces less absenteeism, as is argued in most of the existing literature, or rather a mixture between less absenteeism and more presenteeism. Concerning gender differences, it is well known that absence rates tend to be higher for women than for men. Our data allow us to investigate whether this is also related to moral hazard. On the contrary, we find that females are less likely to be found able to work during the sickness episode, meaning that absence is more likely to be justified by objective health conditions for women than for men.

The remainder of the paper is organized as follows. Section 2 reviews the institutional framework of sickness insurance and monitoring in Italy; Section 3 describes our administrative data and provides a first descriptive analysis; Section 4 presents our analysis and comments on our findings. Finally, Section 5 concludes.

2. Institutional framework

In this section we outline the main features of the Italian system of insurance against income losses due to sickness. The focus will be on the rules that are relevant for private employees, i.e., the only category of workers recorded in our dataset[3]. In describing aspects specific to monitoring activities, the focus of the present work, we will also briefly refer to monitoring policies adopted in other countries.

2.1. Sickness insurance in Italy

The main characteristics of the Italian system are similar to those of most European countries; for a comparative analysis see, among others, Heymann et al (2009) and Scheil-Adlung and Sander (2010). A relevant aspect for our study is that both the public insurer and the private employer play an important role within the system. The public insurer is the National Institute for Social Security, commonly known as INPS *(Istituto Nazionale della Previdenza Sociale).* INPS is in charge of the management of benefits and, as will be discussed in detail below, is a key player in the monitoring process.

In order to be entitled to the benefit, the employee needs to obtain a medical certificate, which must be forwarded to INPS within two days. The certificate is issued by a physician – usually a general practitioner (GP) – and reports information on the sickness and the number of days for which the employee cannot work. The last piece of information is shared with the employer.

The employer pays the full wage during the first three days of absence. Public insurance starts from the fourth day of the sickness episode and can be paid until up to six months. It covers one half of earnings until the 20th day and one third since the 21st day. However, according to virtually all labor contracts, the employer tops-up this amount to compensate for the whole potential income loss.

2.2. Monitoring

In this paper we use the term “monitoring”, at a general level, to refer to any action that is taken within the insurance system to check the health status of a worker during a sickness

[3] The system of insurance for public sector employees is somewhat different. For instance, the monitoring is due in some circumstances, and, when it is deliberately asked, only the employer can do that. See De Paola et al. (2014) for an analysis of a recent reform in the public sector.

spell. For Italy, this is based on a medical visit, whose outcome is the focus of our empirical analysis. One may wonder why a new visit is needed given that in most cases the entitlement to the allowance is already stated by a physician. This is related, among other things, to the informational advantage that the patient may have for some health conditions that are hard to verify objectively. Markussen et al. (2011) report evidence of substantial variations in certification practices across physicians and conclude that the room for subjective judgment is large[4]

In order to be eligible for the payment of a sick leave, each employee is required to remain at her home address for four hours a day (from 10 am to noon and from 5 pm to 7 pm) during each day of the leave. This requirement is related to the possible occurrence of a new medical visit – in addition to the one after which the physician issued the certificate that entitled the worker to the allowance – as the main monitoring tool. The employee's absence from home can be excused only for extraordinary circumstances, such as medical emergency regarding the individual or her family. Otherwise, it is punished with a cut in the allowance, which is greater if the employee had already not been found at home before. The aim of the visit is to check whether the health of the employee is such that she is actually unfit to work for the number of days reported in the certificate. At the end of the home visit, the physician can either confirm the inability to work until the time reported in the original certificate, or decide that the employee is now fit and can return to work within three days after the visit. If the sick leave expires within three days anyway, "ability to work" prevents the worker from extending the current sickness spell with a new certificate. As a result the physician acts as a gatekeeper for the continuation of the sickness episode in this circumstance.

A peculiarity of the system is that either INPS or the employer can decide to monitor a sickness episode. In order to do so, the latter needs to pay a fee, which is of approximately 60 euros per visit.[5] Importantly, since also employers' monitoring requests are managed by INPS, the group of physicians who execute visits is the same in both cases and the employer cannot choose the physician, who is randomly selected among those with

---

[4] See also Askildsen et al. (2005) and Larsen et al. (1994) on this point.

[5] The fee is made of a fixed part and a variable part depending on travelling costs. In the period under investigation the fixed part amounts to 41.67 euros in weekdays, and 52.82 euros in weekend days. The variable part is proportional to the distance in kilometers between the address of the physician and the address of the employee, with a minimum of 6 euros.

a free schedule. Until 2010 visits sent by INPS were selected on a purely random basis; since 2011 a data mining software is available to support the decision on whom to visit, although the final decision is still made by the person responsible of the selection of the cases to monitor. Based on a time series of past sick-leave certificates and visits, the software attaches a score to each certificate. The score is meant to estimate the probability that the employee presenting the certificate is actually able to work. However, digital certificates also became mandatory since January 2011 (Health Ministry Decree, D.lgs. 150/2009), which means that the software was initially useless as no or few data were available for the score estimate.

Italy is not the only country where the employer is allowed to play an active monitoring role. Employer’s monitoring looks reasonable for at least three reasons. First, the employer acts as an insurer together with the social insurer in virtually all countries, although the length of the period and the proportion of the cost borne may vary substantially across countries. Second, the employer bears organizational costs in addition to the direct costs of insurance. Third, the employer may be expected to have better, although still imperfect, information on the employee's true health conditions. In Germany, for example, the employer can make a motivated request for a check of the employee’s inability to work by an expert from the medical service of the health insurance company. The employee cannot refuse the check if requested by the health insurance’ medical service. In the UK, under some conditions (e.g., more than four short periods of sick leave in a year), employers can request a monitoring action by Medical Services. This involves a consultation with the employee’s GP, for which the employee's consent is required. In case the Medical Services conclude that the employer could have worked, given her health condition, the employer may decide not to pay for the days of work missed.

3. Data

We use administrative data, kindly provided by INPS, regarding the population of private-sector employees living in the district of Verona (North-eastern part of Italy), who received at least one official medical visit at home after submitting a job sick leave certificate between January 2009 and December 2014.[6] Over this period, INPS received 1,167,109 sick leave certificates and made 113,733 visits (autonomously or on behalf of employers).[7]

In the empirical analysis we focus on visits that were actually made.[8] We also exclude visits regarding atypical workers older than 64 and visits with incomplete records. The final sample, including information on all the variables we consider, is made of 92,050 visits on 48,801 workers (roughly 12% of the working population in the district of Verona).[9]

Table 1 shows summary statistics on the variables we use from the dataset. The average visited person is 41.38 years old; 18.4% of the visited workers are foreigners (mainly from Romania and Morocco), and 38.6% are females. The average sick leave length in our dataset is 14.30 days (weekends included), although it is highly heterogeneous and can vary between 1 and 180 days. About half of the visits (54.8%) concern workers who had been already visited at least once before; in 9.3% of the cases the visit also comes after another visit on the same worker and for the same illness. Nearly 75% of the visits involve workers who had already had another sick leave before, and in about 21% of the cases a previous sick leave expired no earlier than three days before the current sick leave. We can interpret it as a continuation of the same sick leave. Slightly more than 3 visits out of 4 are made within the last 3 days of sickness, i.e., in the situation where the physician acts as a gatekeeper – to assess whether there are the conditions for the worker to exhibit further certificates and continue the same sickness episode. In our analysis we also control for the physician who made the visit, the year, the quarter, the national unemployment rate in the previous month[10] and the number of visits in the previous twelve months (from either INPS or the employer). This variable is meant to capture the role of the probability of monitoring as perceived by the employee as a possible explanation of changes in opportunistic behavior.

[6] INPS moved to digital documents in January 2011. Earlier data have been digitalized from originally handwritten official certificates.

[7] From informal discussions with INPS officers we learnt that backache and influenza are the most common types of illness reported in the certificates. Officers, however, are not required to include this information in the administrative database.

[8] A visit is not made when the worker is not found at home, or when the declared home address is wrong. In our raw data this happens in around 8% of the cases.

[9] The number of employed workers in the district is estimated around 400,000. This is derived after multiplying the number of resident individuals in age 15-64 in 2011 in the district (source: http://demo.istat.it/pop2012/) by the employment rate in the same year (source: www.vr.camcom.it).

[10] The source is the National Institute of Statistics, ISTAT. The institute also provides a series on the district level at an annual frequency. Results are similar if we employ the latter measure (that is systematically lower since the district is relatively richer than the average of the country).

TABLE 1 ABOUT HERE

Employers require visits less frequently than INPS (in just 18% of the cases). However, when looking at the time trend of the number of visits (Figure 1) we see that employers requested a roughly stable number of visits over time (between 200 and 300 per month), while INPS progressively increased its number of visits up to May 2012, when it reached a peak at 2,207 visits per month, and then cut visits; since May 2013 the number of visits directly sent by INPS was around 300 on average.[11]

FIGURE 1 ABOUT HERE

This time trend in the number of visits follows a specific policy of INPS, that first decided to devote more effort on medical visits, as a means of both preventing and detecting opportunistic behavior by workers, and then had to limit visits because of a budget cut from the government. Moreover, it should be recalled that, starting from January 2011, decisions by INPS on whom to monitor were supported by a data mining software. However, as reported in Sub-section 2.2, the data mining software became only progressively operational as more digital data accumulated. The two main events (data mining software and budget cut) arisen in the period under investigation are sketched in Figure 2.

FIGURE 2 ABOUT HERE

About 1 visit out of 3 ends up in declaring the worker able to work. Figure 3, that compares the percentage of workers found able to work over time, informs us that the percentage: i) tends to grow over time; ii) is subject to seasonality, with peaks in the winter months; iii) is higher if the visit is requested by the employer (at least before May 2013).

FIGURE 3 ABOUT HERE

[11] In the period October-December 2013 INPS made no visits at all because at that time it had already exhausted all of its annual budget for visits.

Table 2 shows summary statistics for our variables separately for visits sent by INPS and visits requested by the employer, and for visits made before and since May 2013, i.e., before and after the cut in the INPS budget for home medical visits. We first look at the sample period from January 2009 to April 2013. In this period INPS selected which workers to visit on an essentially random basis, in contrast to employers that were free to autonomously choose whether and whom to visit. This notwithstanding, we see from Table 2 that the demographic characteristics of the workers are similar in the two sub-samples (and, apart from age, statistically equal according to a mean comparison t-test[12]). This may suggest that employers do not exhibit prejudice against some particular types of worker (e.g., foreigners). In contrast, employers on average select for a visit workers under a shorter sick leave (10.64 against 15.43 days) and, more often than INPS, workers who had already been visited in the past or for the same sickness episode. The proportion of visits ending with a declaration of being able to work is higher among those requested by the employer (47.8 vs. 34%). Given that visit selection was random, we can interpret the outcome of INPS visits (34%) as an indication of the fraction of workers that can return to work. When looking at the sample period since May 2013, we see that on average visits made by INPS ended up more frequently than visits requested by employers in declaring job ability (51.5% as opposed to 44%). In contrast to statistics before May 2013, we also see that INPS sent visits more frequently on the last three days of sickness (in 92.1% of the cases) and visited workers with an average sick leave length similar to employers (10.55 instead of the 10.68 days on employer visits). This may be the result of choosing the workers to visit based on the data mining software rather than randomly. To support this interpretation, the average of the variables in Table 2 is not different over the two periods for visits made on behalf of the employer, for whom, unlike for INPS, the selection process has remained the same.

TABLE 2 ABOUT HERE

[12] We run t-test on the equality of the mean in the two groups of visits requested by employers and INPS, before May 2013. For age: t-test: -5.74, p-value <0.01; for gender, t-test: -0.94, p-value: 0.35; for nationality: t-test: -0.89, p-value: 0.37.

4. Analysis

The analysis is based on a set of probit regressions reported in Table 3, where the observation unit is the single home medical visit. We do not exploit the panel dimension of the dataset, as in most cases we have just one or two observations per worker. However, we use standard errors clustered at the worker level to allow for possible within-group correlation. In all the cases the dependent variable is a binary variable equal to 1 if the physician declares the employee able to work, and 0 otherwise. The specification includes a number of explanatory and control variables. The explanatory variables vary across the columns of Table 3, while as control variables we always consider if the visit was made within the last three days of sickness, the unemployment rate in the previous month, the number of visits in the previous twelve months, quarter, year and physician dummies. These variables are expected to capture all the variation due to time trend, seasonality and subjective judgment of the physician. The table reports average marginal effects.

4.1. Employers' and public insurer's visits

In Column (1) of Table 3 we take as explanatory variable, in addition to the control variables, only one binary variable informing on whether the visit was requested by INPS rather than the employer. We find a large and significant effect, as it turns out that visits requested by INPS are 8.3% less likely to declare a worker able to work. A possible explanation for this result is that employers are better informed than INPS about their employees and for this reason they request visits on workers that are indeed more likely to cheat about their health. Regarding the control variables, we notice a large and significant effect of the decision to send a visit within the last three days of leave (+51.6%).

In our data, visits were randomly chosen only for INPS in the first part of the sample period: visits were otherwise chosen based on observed information. To control for this, Columns (2) and (3) include in the specification further explanatory variables. Column (2) adds information on the length of the sick leave, and two binary variables informing on whether the worker had been already visited in the past, generically or for the same sick leave. We also include two binary variables on whether the worker ever exhibited a sick leave certificate in the past, and whether she was in sick leave until up to three days before the current leave.

The five variables show strongly significant effects. In particular, the probability to be declared able to work is 1.35% lower with a 10% increase in the days of sick leave. This is in line with the theoretical and empirical literature that treats long-term sickness absence as structurally different from short-term absence (Gilleskie, 2010). The probability of being declared able to work is also 6.6% lower for workers already visited for the same sick leave and 4.7% lower for workers with another sick leave up to no more than three days before the current leave. Already visited workers and workers who are not new at sick leave experiences are possibly seen suspiciously and they are therefore more likely to be visited. However, the analysis suggests they do not do worse than others; actually, these workers are less likely to be considered able to work. Interestingly, the inclusion of information on visits and sicknesses largely improves the fit of the model (in terms of both pseudo-R^2 and count-R^2, i.e., the percentage of correctly predicted observations) and makes the effect of the binary variable on the employer/INPS visit request much smaller although still significant (2.9% as opposed to 8.3% from Column (1)). This reduction of the effect suggests that employers are more effective than INPS in selecting the workers to visit (also see the descriptive statistics in Table 2). In particular, on average employers request a visit on workers in a shorter sick leave, at least in the first part of the sample period, which tends to be associated with a higher probability of finding the worker able to work.

4.2. Worker's characteristics

Column (3) adds to the specification further demographic variables on the worker (age, gender, nationality). To allow for possible non-linear effects, age is split in three brackets, where the reference category is the 51-64 age bracket. The output shows that the probability to be declared able to work after a home medical visit is higher for young individuals (+4.9% for those aged 35 or less compared to those aged 51-64), and lower for foreigners (-1.8% compared to Italians) and females (-2.3%).

In particular, regarding gender, it is well known that absence rates tend to be higher for women. A number of hypotheses have been tested in the literature, which can be roughly split into economic (noticeably, family responsibilities) and health issues (Paringer, 1983). Our finding that women are no more (in fact less) likely to be found able to work during a sickness episode favors the second hypothesis, and it is therefore in line with the results obtained, for example, by Paringer (1983) and Vistnes (1997). An important difference with those contributions is that our health status measure is not self-reported, but assessed through a medical visit.

The effects of the remaining variables are preserved, both qualitatively and quantitatively. Although significant[13], the newly added variables have a small effect on the probability to be declared able to work, with the only exception of being 35 years old or younger. In addition, the fit of the model in Column (3) is only marginally better than the one in Column (2), which excluded the demographic characteristics of the worker.

In Columns (2) an (3) we find an insignificant effect of the unemployment rate and a significantly negative effect of the number of visits in the previous twelve months: from Column (3), in particular, we find that a 10% drop in the number of annual visits would increase by 0.5% the probability of being found able to work. The effect is small, but it is interesting from a policy perspective to notice that its sign is coherent with a potential opportunistic behavior of the workers: they are moderately responsive to a change in the probability of being detected.

4.3. Policy changes

Since January 2011, INPS had the possibility to use a data mining software and, at least in principle, make a selection of the employees to visit based on objective criteria. The software associates a score to each sick leave episode, obtained from observable information on the worker and the sick leave. The software uses the same information as in this paper, since the data source is identical. The score is increasing in the predicted probability of finding the worker "able to work". To account for potential effects due to the software advice we repeat in Column (4) of Table 3 the same analysis as in Column (3), where the "INPS request" binary variable is now split in two new variables, depending on whether the visit was made before or since January 2011, i.e., without or with the data mining software available. The baseline category is still the employer's visit request.

We find that, compared to visits requested by the employer, those chosen by INPS before (since) January 2011 are 4.7% (1.8%) less likely to end with a declaration of ability to work. The two effects before and since January 2011 are statistically different from each other according to a comparison test (Chi-squared test: 11.37, p-value <0.01). Hence INPS,

[13] The fact that many variables are significant is also due to the large sample size: with a large dataset, even a small difference turns out to be significant. In this context, it is the lack of significant effects to be more interesting.

when the software became available, improved the efficiency of its visits, but remained less effective than employers in selecting whom to visit. A possible explanation is that, as we already mentioned, the time series of historical data on visits – necessary for data mining – was not immediately available but started being built in 2011.

Following a reduction in the funds coming from the central government, starting in May 2013 INPS made a drastic cut in the budget for the medical visits it autonomously sent. In an effort to make the fewer visits more efficient, the decision on whom to visit relied more heavily on the data mining software that, at that moment, was able to run on a time series of nearly two years and one half of data. This software provides a tool to choose whom to visit, even though its indication is not stringent and the person in charge of the decision is free to ignore it.

Column (5) of Table 3 replaces the binary variable for INPS requests with data mining (i.e., since January 2011) with two new binary variables, for INPS requests made between January 2011 and April 2013 (with data mining software but before the budget cut) and since May 2013 (with the software and after the budget cut). The baseline category is still the visit requested by the employer. The column informs that the new policy implemented by INPS since May 2013 was effective, as INPS was finally able to reach a performance even better than that of employers (+2.4% in the probability to detect ability to work). The finding suggests the validity of the new strategy to base the decision on whom to visit relying on a software rather than pure randomness.

4.4. Unemployment

We conclude the section with a focus on unemployment. Most of the literature documents a negative correlation between unemployment and absence rates (e.g., Askildsen et al., 2005). We argue that being able to control for employee's health status is crucial for a sound understanding of the underlying mechanism. Figure 4 helps to illustrate the idea. Panel a) shows a hypothetical base scenario where the sum of the two rectangular areas corresponds to the number of individuals not working, which is made up of those actually sick ("unable to work") and those who would be "able to work". The latter group would be ideally identified if monitored through a visit.

FIGURE 4 ABOUT HERE

Panels b) and c) both refer to a situation where unemployment increases and absences fall (the gray areas denote individuals not going on sick leave because of the higher unemployment rate), the only difference between them being that in b) there is less shirking (fewer individuals able to work are in sick leave), whereas in c) there is more presenteeism (more individuals unable to work choose to work nonetheless). In both cases one would find a negative correlation between unemployment rates and absence rates, as is typically the case in the literature. However, data on days of work lost would not allow to distinguish between the two phenomena, which are completely different in terms of both economic and public health implications. On the contrary our data, measuring the probability to be found able to work, would show a negative sign for the unemployment rate covariate if shirking prevails (panel b; the fraction of those "able to work" among those in sick leave grows) and a positive sign if presenteeism dominates (panel c; the fraction of those able to work among those in sick leave falls).

From a policy perspective it is interesting to notice that, only in the last specification of Column (5), the unemployment rate shows a negative correlation with the probability of being declared able to work: the probability falls by 4% with a 1% increase in the unemployment rate. Our result from Column (5) thus suggests that the shirking force is prevailing. However, we cannot draw the same conclusion from the other specifications of Table 3, which seem to indicate that both shirking and presenteeism forces are in action and play an opposite role with similar size.

TABLE 3 ABOUT HERE

5. Concluding remarks

Within the Italian system of insurance against sickness related income losses, monitoring is based on medical visits at employee's home that can be either requested by the public insurer (INPS) or the employer. in this paper we use a large administrative dataset containing, among other information, the outcome of the visit, with the primary objective of comparing the performance of alternative monitoring regimes.

We find a number of interesting results. First, before May 2013 visits requested by employers were more effective in detecting ability to work than visits autonomously (and randomly) sent by INPS, probably because of an informational advantage. Second, the effectiveness of employer visits was the result of a better selection of the workers to visit, based primarily on the length of the sick leave. Third, the performance of the public insurer is in line with the employer's one since May 2013, after controlling for observable characteristics. This is the period when the number of visits was significantly reduced, and the allocation more strongly supported by an algorithm based on statistics on past visits. The message we take from these findings is that the public insurer can perform as well as the private insurer, thus compensating for the employer's informational advantage, when the number of visits requested is similar and a formal algorithm supports the decision on whom to monitor.

Concerning our second objective – investigating the impact of using a direct measure of health on the study of opportunistic behavior – we find weak evidence that the correlation between unemployment rate and the probability of being found able to work is significantly negative. This evidence is in line with existing literature finding that absenteeism is more limited when unemployment rates are higher (Askildsen et al. 2005). However, this evidence emerges in only one of our analyses, whereas in all the others the probability of being found able to work turns out to be uncorrelated with the unemployment rate. This result is more compatible with the view that a higher unemployment rate induces both less absenteeism and more presenteeism, where the latter means that more people choose to work despite a poor health condition (e.g., Chatterji and Tilley, 2002). Our data also suggest that the well known higher rate of female absence from work is attributable to health rather than economic conditions (such as family responsibilities), as already found for instance in Paringer (1983) and Vistnes (1997) using self-reported health status measures.

An interesting avenue for future studies consists in combining data on visits with administrative data on sick leave certificates. This would allow to better understand the criteria under which a worker is chosen for a visit. In addition, the availability of a long time series of certificates could shed more light on the effect in workers' behavior of knowing that visits are less frequent (since May 2013) and on the issue of absenteeism and presenteeism during the financial crisis. Did workers change their behavior with respect to sick leaves during the crisis? Did they choose to work even when sick (presenteeism) or did they choose to stay at home in sick leave more often or for more time (absenteeism)? These questions are left to future research.

References

Askildsen, J.E., Bratberg, E., and Nilsen, Ø.A. (2005),"Unemployment, Labor Force Composition and Sickness Absence: A Panel Data Study," *Health Economics*, 14(11), 1087-1101.

Barmby, T., Ercolani, M.G., and Treble, J.G. (2002), "Sickness Absence: An International Comparison," *Economic Journal*, 112(480), F315-F331.

Böheim, R., and Leoni, T. (2014), "Firms' Sickness Costs and Workers' Sickness Absences," NBER Working Paper No 20305, National Bureau of Economic Research.

Chatterji, M., and Tilley, C.J. (2002), "Sickness, Absenteeism, Presenteeism, and Sick Pay," *Oxford Economic Papers*, 54(4), 669-687.

Coles, M.G., Lanfranchi, J., Skalli, A., and Treble, J. (2007), "Pay, Technology, And The Cost Of Worker Absence," *Economic Inquiry*, 45(2), 268-285.

Coles, M.G., and Treble, J.G. (1996), "Calculating the Price of Worker Reliability," *Labour Economics*, 3(2), 169-188.

De Paola, M., Scoppa, V., and Pupo, V. (2014), "Absenteeism in the Italian Public Sector: The Effects of Changes in Sick Leave Policy," *Journal of Labor Economics*, 32(2), 337-360.

Dew, K., Keefe, V., and Small, K. (2005), "'Choosing' to Work when Sick: Workplace Presenteeism," *Social Science & Medicine*, 60(10), 2273-2282.

Engström, P., and Johansson, P. (2012), "The Medical Doctors as Gatekeepers in the Sickness Insurance?," *Applied Economics*, 44(28), 3615-362.

Flåm, S.D. (2004), "Social Insurance of Short Spell Sickness," *Nordic Journal of Political Economy*, 30, 79-90.

Gilleskie, D.B., (2010), "Work Absences and Doctor Visits during an Illness Episode: The Differential Role of Preferences, Production, and Policies among Men and Women," *Journal of Econometrics*, 156(1), 148-163.

Hartman, L., Hesselius, P., and Johansson, P. (2013), "Effects of Eligibility Screening in the Sickness Insurance: Evidence from a Field Experiment," *Labour Economics*, 20, 48-56.

Herrmann, M.A., and Rockoff, J.E. (2012), "Does Menstruation Explain Gender Gaps in Work Absenteeism?," *Journal of Human Resources*, 47(2), 493-508.

Heymann, J., Rho, H.J., Schmitt, J., and Earle, A. (2009), "Contagion Nation- A

Comparison of Paid Sick Day Policies in 22 Countries," CEPR Reports and Issue Briefs No 2009-19, Center for Economic and Policy Research (CEPR).

Heywood, J.S., Jirjahn, U., and Wei, X. (2008), "Teamwork, Monitoring and Absence," *Journal of Economic Behavior & Organization*, 68(3-4), 676-690.

Ichino, A., and Moretti, E. (2009), "Biological Gender Differences, Absenteeism, and the Earnings Gap," *American Economic Journal: Applied Economics*, 1(1), 183-218.

Johns, G. (2010), "Presenteeism in the Workplace: A Review and Research Agenda," *Journal of Organizational Behavior*, 31, 519-542.

Khan, J., and Rehnberg, C. (2009), "Perceived Job Security and Sickness Absence: a Study on Moral Hazard," *European Journal of Health Economics*, 10(4), 421-428.

Larsen, B.A., Forde, O.H., and Tellnes, G. (1994) "Legens kontrollfunksjon ved sykmelding," *Tidsskrift for Den Norske Lægeforening*, 114(12), 1442-1444.

Leigh, J.P. (1985), "The Effects of Unemployment and the Business Cycle on Absenteeism," *Journal of Economics and Business*, 37(2), 159-170.

Markussen, S., Røed, K., Røgeberg, O.J., and Gaure, S. (2011), "The Anatomy of Absenteeism," *Journal of Health Economics*, 30(2), 277-292.

Olsson, M. (2009), "Employment Protection and Sickness Absence," *Labour Economics*, 16(2), 208-214.

Paringer, L. (1983), "Women and Absenteeism: Health or Economics?," *American Economic Review*, 73(2), 123-127.

Pauly, M.V., Nicholson, S., Polsky, D., Berger, M.L., and Sharda, C. (2008), "Valuing Reductions in On-the-job Illness: 'Presenteeism' from Managerial and Economic Perspectives," *Health Economics*, 17(4), 469-485.

Pfeifer, C. (2013), "Cyclical Absenteeism Among Private Sector, Public Sector And Self-Employed Workers," *Health Economics*, 22(3), 366-370.

Pichler, S. (2014), "Sickness Absence, Moral Hazard, and the Business Cycle," *Health Economics*, forthcoming.

Pichler, S., and Ziebarth, N.R. (2015), "The Pros and Cons of Sick Pay Schemes: A Method to Test for Contagious Presenteeism and Shirking Behavior," IZA Discussion Paper No 8850, Institute for the Study of Labor.

Scheil-Adlung, X., and Sandner, L. (2010), "Evidence on Paid Sick Leave: Observations in Times of Crisis," *Intereconomics*, 45(5), 313-321.

Vistnes, J.P. (1997), "Gender Differences in Days Lost from Work Due to Illness," *Industrial & Labor Relations Review*, 50(2), 304-323.

Waehrer, G.M., and Miller, T.R. (2003), "Restricted Work, Workers' Compensation, and Days Away from Work," *Journal of Human Resources*, 38(4), 964-991.

Weiss, A.M., (1985), "Absenteeism and Wages," *Economics Letters*, 19(3), 277-279.

Ziebarth, N.R., and Karlsson, M. (2014), "The Effects Of Expanding The Generosity Of The Statutory Sickness Insurance System," *Journal of Applied Econometrics*, 29(2), 208-230.

Table 1. Sample statistics (90,250 observations)

	Mean	Std.dev.	Min.	Max.
Able to work	0.373	0.483	0	1
INPS request	0.820	0.385	0	1
Worker				
Age	41.379	10.316	16	64
Female	0.386	0.487	0	1
Foreign	0.184	0.387	0	1
Visit and sickness				
Days sick leave	14.302	15.738	1	180
Already visited in the past	0.548	0.498	0	1
Already visited for this sick leave	0.093	0.290	0	1
Already sick leave in the past	0.738	0.440	0	1
Already sick leave until 3 days ago or less	0.213	0.409	0	1
Control				
Visit during last 3 days	0.789	0.408	0	1
Unemployment rate previous month (%)	9.026	1.629	6.846	12.637
Number of visits previous 12 months	21,214.340	5,567.209	4961	28,140
Year	2011.185	1.466	2009	2014

Table 2. Sample statistics by sender and time period

	Before May 2013		Since May 2013		
Sample	**Employer**	**INPS**	**Employer**	**INPS**	**All**
Able to work	0.478	0.340	0.440	0.515	0.373
INPS request	0	1	0	1	0.820
Worker					
Age	41.040	41.624	42.369	37.852	41.379
Female	0.385	0.389	0.385	0.343	0.386
Foreign	0.179	0.182	0.171	0.222	0.184
Visit and sickness					
Days sick leave	10.644	15.425	10.679	10.548	14.302
Already visited in the past	0.656	0.528	0.755	0.382	0.548
Already visited for this sick leave	0.161	0.085	0.129	0.004	0.093
Already sick leave in the past	0.653	0.774	0.668	0.501	0.738
Already sick leave until 3 days ago or less	0.091	0.255	0.062	0.050	0.213
Control					
Visit during last 3 days	0.831	0.770	0.827	0.921	0.789
Unemployment rate previous month (%)	8.470	8.686	12.132	12.550	9.026
Number of visits previous 12 months	21,883.880	22,544.440	12,504.440	8,168.766	21,214.340
Year	2010.705	2010.931	2013.554	2013.923	2011.185
Observations	*12,043*	*69,131*	*4,241*	*4,835*	*92,680*

Table 3. Detecting deception

	(1)	(2)	(3)	(4)	(5)
INPS request	-0.083***	-0.029***	-0.029***		
	(0.004)	(0.005)	(0.005)		
INPS request				-0.047***	-0.048***
without data mining				(0.008)	(0.007)
INPS request				-0.018***	
with data mining				(0.005)	
INPS request					-0.031***
with data mining and before the budget cut					(0.006)
INPS request					0.024**
with data mining and after the budget cut					(0.010)
Worker					
Aged 35 or below			0.049***	0.049***	0.048***
			(0.004)	(0.004)	(0.004)
Aged between 36 and 50			0.026***	0.026***	0.026***
			(0.004)	(0.004)	(0.004)
Female			-0.023***	-0.023***	-0.022***
			(0.003)	(0.003)	(0.003)
Foreign			-0.018***	-0.018***	-0.018***
			(0.004)	(0.004)	(0.004)
Visit and sickness					
Ln(days sick leave)		-0.135***	-0.133***	-0.133***	-0.132***
		(0.003)	(0.003)	(0.003)	(0.003)
Already visited in the past		-0.028***	-0.025***	-0.025***	-0.024***
		(0.003)	(0.003)	(0.003)	(0.003)
Already visited for this sick leave		-0.066***	-0.067***	-0.068***	-0.068***
		(0.006)	(0.006)	(0.006)	(0.006)
Already sick leave in the past		-0.013***	-0.013***	-0.013***	-0.012***
		(0.004)	(0.004)	(0.004)	(0.004)
Already sick leave until 3 days ago or less		-0.047***	-0.047***	-0.047***	-0.047***
		(0.004)	(0.004)	(0.004)	(0.004)
Control					
Visit during last 3 days	0.516***	0.400***	0.400***	0.400***	0.399***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Unemployment rate previous month (%)	0.015	-0.016	-0.019	-0.025	-0.040**
	(0.019)	(0.018)	(0.018)	(0.018)	(0.018)
Ln(visits previous 12 months)	-0.030*	-0.048***	-0.047***	-0.053***	-0.039***
	(0.016)	(0.015)	(0.015)	(0.015)	(0.015)
Quarter dummies	YES	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES
Physician dummies	YES	YES	YES	YES	YES
Observations	90,250	90,250	90,250	90,250	90,250
Log-likelihood	-50,898.231	-48,834.818	-48,727.469	-48,720.772	-48,707.926
Count-R^2	0.669	0.708	0.710	0.710	0.710
McFadden Pseudo-R^2	0.146	0.181	0.182	0.182	0.183

*Note: The table reports average marginal effects obtained from probit regressions. Standard errors in parentheses are clustered by worker; *** p<0.01, ** p<0.05, * p<0.1*

Figure 1. Time trend in the number of visits

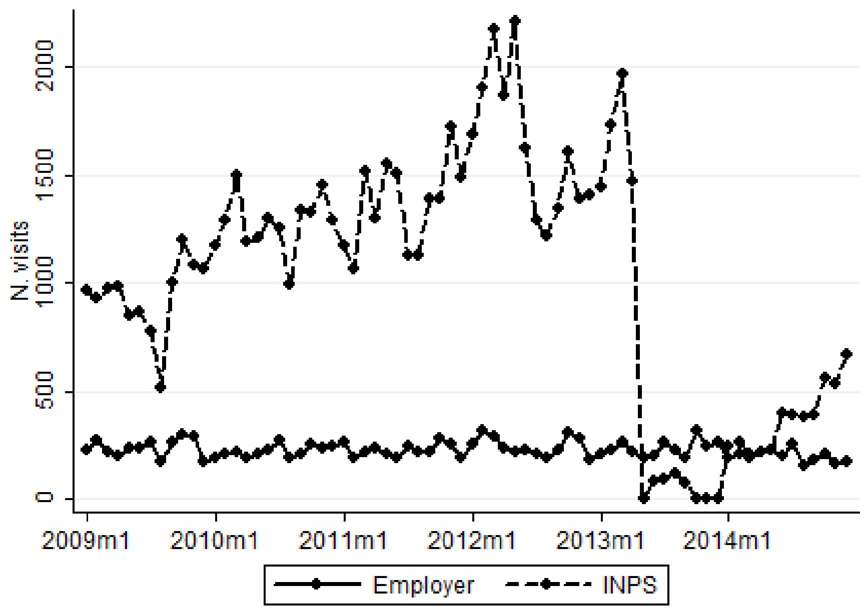
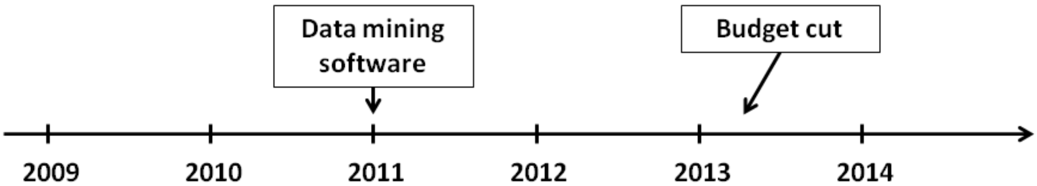


Figure 2. Environment



Note: INPS adopted a data mining software since January 2011, and experienced a budget cut for home medical visits since May 2013.

Figure 3. Time trend in the percentage of visits ending with "ability to work"

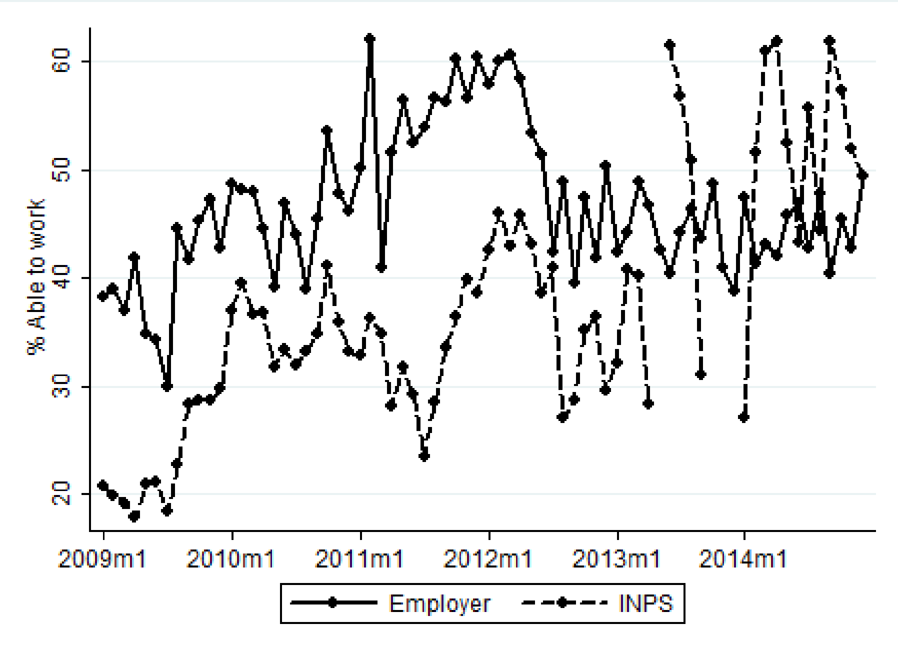
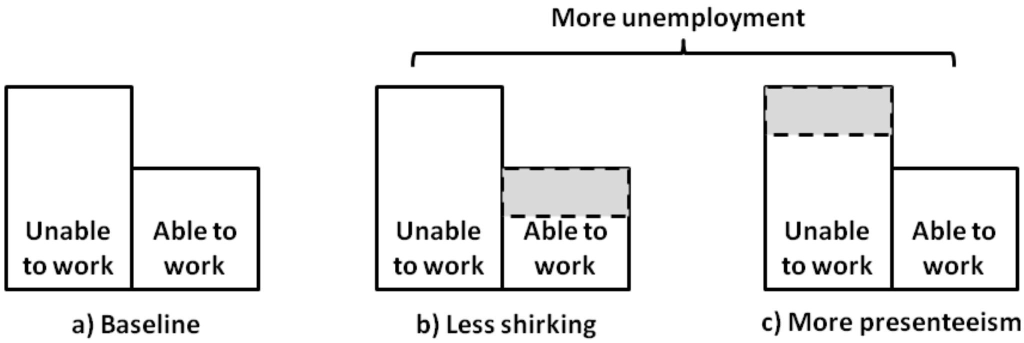


Figure 4. Absence and unemployment rate



Note: Gray areas denote individuals not going on sick leave because of a higher unemployment rate.