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Sick Pay and Absence from Work: Evidence from Flu Exposure

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Abstract

The system of sick-pay is critical for balancing the economic and health costs of infectious diseases. Surprisingly, most research on sick-pay reforms does not rely on variation in worker exposure to diseases when investigating absences from work. This paper studies the effects on absences from work of changes in health-insurance coverage of the first three days of sickness. We explore geographic variation in the prevalence of infectious diseases, primarily the seasonal flu, to provide variation in the need for sickness insurance. Estimates based on the Czech Structure of Earnings Survey imply that when sickness insurance is not available, total hours of work missed are not affected, but employees rely on paid and unpaid leave instead of sick-leave to stay home. The substitution effects are heterogenous across occupations and socio-demographic characteristics of employees, and suggest that workers do not spread infectious diseases at the workplace as a result of the absence of sickness insurance coverage in the first three days of sickness.

Keywords: Sickness insurance, exposure to sickness, policy reforms, Czech Republic.

JEL Classification: I13, I18, J3.

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1 Introduction

Most European countries provide workers with sick-pay benefits if they experience a temporary sickness. Such insurance allows sick employees to pay their regular expenses when they are not able to work. In the optimal scenario, employees stay home when they are ill and avoid spreading their disease to coworkers, and return to work once they are healthy, without shirking. They also do not experience adverse long-term health effects from not treating their diseases.[1] The design of sick-pay programs have a substantial influence on employees' decisions to stay at home/go to work. Decreases in sick-pay benefits may either reduce shirking or result in employees going to work when they are sick, a typical moral hazard problem. Thus, it is important to understand and measure the effects of sick-pay programs, as they are associated with significant financial and health costs.[2]

The literature on workplace absences has so far focused on how individual characteristics affect the probability of being absent from work (e.g., Barmby, 2002; Scoppa, 2010; De Paola, 2010; Amuri, 2011), and analyzed the effects of changes in sick-pay programs (e.g., Ziebarth and Karlsson, 2010; Pettersson-Lidbom and Thoursie, 2013; De Paola et al., 2014; Pertold, 2019). Still, little is known about the relationship between actual sickness rates and absences from work. While a few studies consider health status of workers, (for example, see Ichino and Moretti, 2009; Herrmann and Rockoff, 2010) no study has explicitly linked the relationship between health status, rates of absence from work and how this is affected bz changes in sick-pay programs.

In this paper, we link local sickness rates to employees' records from the Czech

[1]For example, literature finds a strong association between the recent incidence of respiratory infections and major cardiovascular events (Clayton et al., 2008).

[2]For example, money spent on sick pay policies amounted to 1.13 billion EUR (for simplicity, we use a conversion rate 25 CZK/ 1 EUR through this paper) - 28,3 billion Czech crowns (CZK) in the Czech Republic in 2017, which is approximately a 3.6 times higher number than was spent on unemployment policies in that year (Ministry of Labour and Social Affairs, 2017).

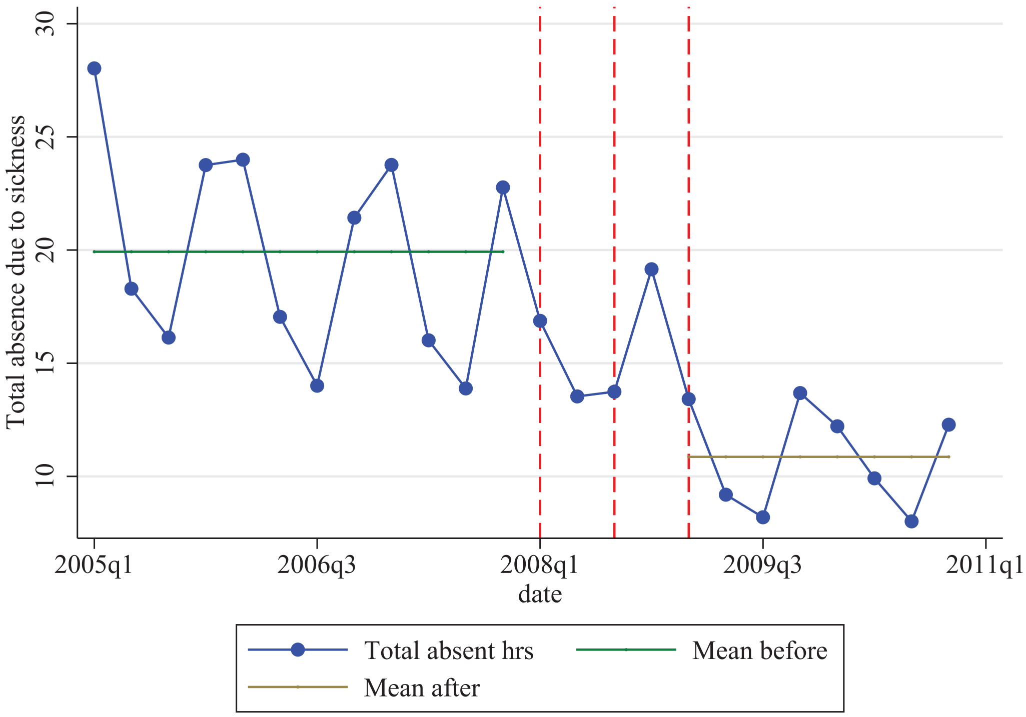
Structure of Earnings Survey (SES), in order to study the impacts of two legislative changes in the Czech sick-pay program during 2008-2009 on absence rates of employees exposed to local infection outbreaks. These policy changes canceled the benefits that participants of the Czech sick-pay program previously received during the first three days of sick-leave.[3] Our analysis measures how the policy changes affected hours absent of employees differently exposed to infectious diseases. A significant decrease in the average sickness-related absences of private-sector employees in Graph 1 (page 4) indicates that the changes did affect the behavior of employees. Our results show that employees took more sickness-related absences when exposed to outbreaks of infectious diseases before 2008 than after the reforms. However, the abolition of sick-pay benefits motivated them to use paid and unpaid leave instead of sick-leave, and resulted in the total hours of absence remaining at their initial levels. To the best of our knowledge, this is the first study that shows how sickness rates relate to absence from work and how changes in the sick-pay system affect the behavior of employees exposed to outbreaks of infectious diseases.

We begin our analysis by showing that there is a positive relationship between the number of hours of absence and local sickness rates. The omission of variables that control for local sickness levels does not necessarily change the explanatory power of the estimated models. However, it may change the size of other estimated coefficients of interest, e.g., the controls for periods after the reforms, which are widely interpreted as the effects of policy reforms in a before-after comparison framework (e.g., De Paola et al., 2014; Pertold, 2019).[4] We first estimate the overall effects of policy reforms using a 'before-after' comparison. A disadvantage of this technique is that the estimates may capture other effects that are unrelated to the policy changes.

[3] The legislative changes are described in Section 2. The first three days of sickness are called a 'quarantine period' or 'waiting period'.

[4] For a demonstration see Table A7.

Figure 1: Sickness absence hours



Note: The graph shows the average quarterly hours of absence per employee before and after the reforms. The red vertical lines indicate the timing of the legislative changes.

Second, we focus on a specific part of the policy reforms' overall effect, and apply an intensity treatment / difference-in-differences identification strategy to estimate how the legislative changes affected absences of employees exposed to specific infectious diseases.[5,6] The *intensity treatment* here refers to an intensity of the need for sickness insurance, i.e., those who were exposed to influenza outbreaks needed the sickness insurance more than those with no exposure. In this setup, the policy reforms did not change the need for sickness insurance among those who were shirking or suffered different diseases than influenza; hence, we strictly focus on changes in hours of absence caused by the lowering of sickness benefits for employees suffering

[5]We cannot apply the standard difference-in-differences estimator as the policy changes affected all employees in the Czech economy.

[6]In most of the estimated specifications, we use a measure of sickness where we count the number of weeks with influenza epidemic status among children, assuming that children can infect adults but not vice versa.

from a specific infectious disease.[7] Using this approach, we estimate very specific local average treatment effects, which bring important insights into the spreading of disease in the workplace. Provided that we observe complete records of different types of hours of absence for each employee, we also bring qualitative evidence on the mechanism behind exposure to influenza and policy reforms.

Our baseline results suggest that one extra week of influenza outbreak among adults prior to 2008 caused an increase in *sickness-related absences* by 5 working days and a decrease in *unpaid leave* by 2 working days. Compared to the situation before 2008, the legislative changes resulted in one extra week of influenza outbreak among adults, decreasing the *sickness-related absences* by 6.7 days (the overall effect becomes negative but statistically insignificant)[8] and increasing *paid* and *unpaid leave* by 1.6 and 2.3 days, respectively (the overall effect became positive). This pattern suggests that as a result of the policy changes, employees exposed to outbreaks of influenza almost perfectly substituted different types of hours of absence (sickness-related absences, un/paid leave). However, the total effect of exposure to sickness among adults remained economically insignificant. We observe a similar substitution pattern when we use a sickness measure that counts the number of weeks with influenza epidemic status among children.[9]

These are important findings regarding moral hazard. One concern could be that canceling sickness benefits would encourage workers to come to work even when they are sick, which would increase the spread of disease at the workplace. Our findings do not support this scenario. However, it is not exactly clear why the moral hazard

[7]Depending on what diseases we use as the exposure measure (influenza, other infectious diseases).

[8]By the "overall effect" we mean the effect of disease exposure in periods after 2008, i.e, the combination of β and γ coefficients from Equation 1 presented in Section 4.

[9]The size of these effects is smaller in the case of *sickness-related absences* but of similar magnitude for *paid* and *unpaid leave*. One extra week of influenza outbreak in periods before 2008 caused an increase in *sickness-related absences* by 1 day and a decrease in *paid* and *unpaid leave* by 1.8 and 1.6 days respectively. The legislative changes enacted caused *sickness-related absences* to decrease by 1.2 days and *paid* and *unpaid leave* to increase by 2.3 and 2.1 days respectively, compared to the initial situation.

behavior is not present; it may be that being sick at work is so uncomfortable that workers prefer to take un/paid leave instead; they are responsible and want to prevent disease spread when they feel unwell. There could also be other reasons behind the substitution pattern.

Using the same identification strategy, based on the varying need for sickness insurance, we examine the relationship between hours of absence and the incidence of other "non-respiratory" infectious diseases, including intestinal infectious diseases, bacterial diseases, etc. For many diseases we find similar substitution effects as in our baseline results; however, the results are economically negligible. Third, we focus on heterogenous effects. Specifically, we estimate the effects separately for mothers and fathers, shift-work occupations, occupations exposed to disease or infections, occupations with high interactions with co-workers, and occupations with high social interactions. In general, the substitution patterns associated with the legislative changes are in the same direction as in our baseline results, though the sizes of the effects differ. Our results suggest that mothers had more sickness-related absences during influenza outbreaks among children prior to 2008, and their response to the reforms was stronger than those of fathers and employees without children. Fathers, however, partially substituted this gap by increasing *paid* and *unpaid leave*. Shift-workers took more *sickness-related absences* and decreased the use of *paid* and *unpaid leave* less when exposed to influenza outbreaks. Furthermore, the effects of the reforms on *paid* and *unpaid leave* were not so strong among shift-workers. We find almost identical results when we classify occupations based on how easily infections spread in specific occupations, how much employees interact with others, and how much social interaction is needed to carry out necessary tasks. We find that occupations in the highest quartile, i.e., those who are the most exposed to infection, used more *sickness-related absences* and more *paid* and *unpaid leave* than the rest of the sample when exposed to influenza outbreaks prior to 2008. We also find that employees highly exposed to the infection decreased *sickness-related absences* more and increased *paid* and *unpaid leave* less as a reaction to the enacted legislative changes. Finally, we ask whether the effects differ by the size of organizational units. We see higher numbers of *sickness-related absences* during influenza outbreaks in organizational units with more employees, which suggests that influenza does indeed spread at the workplace. However, we did not find evidence that the policy reforms reduced or contributed to this spread.

Our paper contributes to several strands of the literature. First, there is only scarce literature on the effects of sick-pay reforms on absenteeism. One explanation could be that it is difficult to find a comparison group of employees who were not affected, which would make it possible to estimate causal effects.[10] Some scholars apply the 'before and after' identification strategy; however, such estimates also capture effects that are not necessarily attributable to the policy reforms. Exploiting the quasi-natural experiment setting, the difference-in-differences identification strategy is used most often (e.g., De Paola et al. (2014); Pettersson-Lidbom and Thoursie (2013); Ziebarth and Karlsson (2010)). Ziebarth and Karlsson (2010) studied the situation in Germany in 1996, when local authorities decreased the level of sickness benefits. This change fully impacted only private sector employees, allowing for the application of the standard difference-in-differences estimation strategy. Their results suggest that the legislative change increased the share of employees with zero sick leave days. A similar methodological approach was applied in Pettersson-Lidbom and Thoursie (2013), who study a legislative change in Sweden in 1987. This reform had two effects: the waiting period of one day was abolished and an income replacement rate for short-term illnesses increased. Pettersson-Lidbom and Thoursie (2013) found that the policy reform increased the share of workers who

[10]Sick pay programs are mainly in effect in small developed countries where the reforms are nation wide.

took additional sick-leave. De Paola et al. (2014) used a modified ‘before and after’ comparison, when they compared differences in days absent in the two periods before and two after the legislative change. They found that a partial wage reduction during the first ten days of sickness decreased the probability of absence. Our study complements preceding work by employing an alternative estimation strategy based on the intensity of exposure to sickness. Instead of focusing on comparing average absences of treated and control groups, or on the periods before and after the reform, we examine the local exposure to sickness. This allows us to compare the absences of employees who were / not exposed to influenza outbreaks. The advantage of this method is that it can be used even if the policy reforms are nation wide.

Second, we supply evidence on the relationship between health status and workplace absences. It is surprising that there is no research that would link sickness rates to absence from the workplace. Studies that consider the health status of employees focus solely on biological gender differences (e.g., Ichino and Moretti (2009); Paringer (1983)).

Third, our paper extends the evidence on changes in sick-pay programs in Central and Eastern Europe. There is limited literature from the Central and Eastern European region. Csillag (2017) studies the effects of a policy change in Hungary in 2011 that caused a 50% decrease in sickness benefits for the top 5% high-earning workers and a 25% decrease for a further 17% of workers. However, the benefits for low-earning workers remained the same. Applying the difference-in-differences estimation strategy, Csillag (2017) finds that the legislative change caused a small reduction in the incidence of absence form the workplace and a significant decrease in the number of days absent among low-earning employees. Pertold (2019) studies the effects of policy reforms in the Czech sick-pay system during 2008-2009, i.e., the same changes that are addressed in this paper. Working with the Czech the SES data, Pertold (2019) uses the ‘before and after’ comparison to find that these legislative changes significantly reduced the number of total days absent. Moreover, Pertold (2019) claims that the effects of the policy changes are extremely heterogenous across industries and occupations, and most affect employees working in manufacturing, hotels, and restaurants. Furthermore, Pertold (2019) shows that employees with more routine tasks and lower job-flexibility are much more likely to reduce their hours of absence.

The paper is structured as follows. Section 2 describes the 2008/09 changes in the sick-pay program. Section 3 describes the main data sources used in our analysis. Section 4 outlines our empirical strategy. Section 5 presents our main results. Section 6 concludes. The majority of graphs and tables can be found in appendix A1.

2 Institutional Context

The system of sick-pay insurance in the Czech Republic covers all salaried employees. The system is obligatory for employees (employers pay the insurance, which is 2.3% of the base salary), and voluntary for the self-employed.[11] The employee contribution is calculated as a share of gross wage with a floor that changes over time. There were two legislative changes during 2008-2009 that affected the sick pay program in the Czech Republic[12], the nature of which offer an interesting setting to study. The first legislation was enacted at the beginning of 2008, lasted only for approximately six months, and was then abolished by the Constitutional Court. At the beginning of 2009, a slightly modified version of the previous Act, which satisfied the objections of

[11]More information on rules and tariffs regarding the sick pay insurance can be found in Act no. 589/1992 Sb..

[12]Currently, the Czech sick-pay system does not include a quarantine period (abolished in July 2019). During an employee's sick-leave, employers pay a contribution that amounts to 2.1% of the base salary. For more information see Act no. 32/2019 Sb..

the Constitutional Court, was implemented. Table 1 summarizes the different stages of legislative changes in the Czech sick pay-program. To reduce the complexity of the sick-pay insurance system in the Czech Republic, we present only information about private sector workers who do not have a signed collective agreement. Extensive information regarding specific cases can be found on the web page of the Ministry of Labour and Social Affairs (2017).

Table 1: Timing of legislative changes enacted

comes into force	January 1, 2004	January 1, 2008	June 30, 2008	January 1, 2009
Stage number	stage 1	stage 2	stage 3	stage 4

Stage 1. Employees received sick pay benefits of 25% of their wage (computed based on the wage records from the past 12 calendar months) during the first three days of sickness i.e., during a so 'called waiting period'. After the first three days of sickness, employees were entitled to standard sick pay provided by the state. Employees who were sick usually received usually around 50-70% of their base wage, mainly based on the reason for the absence.

Stage 2. Employees did not receive any benefits in the waiting period, i.e., for the first three days of absence. They were also obliged to pay sick-pay insurance during the waiting period. After the 3rd day of their absence, employees were entitled to the same remuneration as in stage 1.

Stage 3. The constitutional court decided to abolish the changes that became effective in stage 2. Stage 1 conditions were reinstated.

Stage 4. Employees were not entitled to any sick pay benefits in the waiting period; but they did not have to pay sick-pay insurance in the first three days of their absence. However, the employer became responsible for providing sick-pay benefits in the first 14 days of sickness. From the 15th day, the government provided sick-pay benefits from the sick pay insurance program.

A detailed overview of the current situation across Europe can be found in the

EU´s Mutual Information System on Social Protection (MISSOC) (European Commission's DG for Employment Social Affairs & Inclusion, 2017). The data show that the income replacement rate among European countries varies, but is not lower than 50 percent. Similarly, in the majority of cases, there is a quarantine period, sometimes also called a waiting period, during which an employee does not receive sickness benefits. The most common period in which sickness benefits can be collected is 52 weeks, but this varies substantially between countries. Governments pay out significant amounts of money for sickness benefits; therefore, it is not only in the best interest of employers to have an appropriate sick-pay setting, but all other interested parties, i.e, employees and the public. Our comparison shows that the Czech sick-pay system is similar to other European countries, and thus our results are also relevant to their sickness benefit programs. However, the generalization of our findings to countries with different sickness benefit programs is limited (e.g. developing countries or the US).

3 Data

This section introduces the three main data-sets used in our analysis: the ARI (Acute Respiratory Infections) data on the incidence of influenza and similar respiratory diseases, the EPIDAT (currently ISIN - "Information System on Infectious Diseases") data-set that collects the incidence of infectious diseases except respiratory diseases and HIV, and the ISPV ("Average Earnings Information System") that is the Czech Structure of Earnings Survey (SES). We convert all data to a county-quarter level. We create three age groups (children: 0-14 years old; adults: 15-59; elderly: 60+) that we use consistently through our analysis.

3.1 ARI

We use information on all reported incidences of acute respiratory diseases in the Czech Republic during 2005-2012, which amounts to approximately 1/2 of the total number of sickness spells per year.[13] The data-set contains the counts of weekly incidence of respiratory diseases by age group, gender, and the county where a sickness spell was reported. The type of data does not allow us to rule out the possibility that we might observe the same person several times in different weeks during the same quarter.

Graph A1 shows the evolution of incidences of influenza in Czech counties. Influenza is highly seasonal and children and teenagers are most affected. The incidence of respiratory diseases was approximately constant during 2005-2012 and there were no major drops in sickness around the time when the legislative changes affecting the sick-pay program were implemented. Table A1 compares the average incidence of acute respiratory diseases across counties in periods before and after the legislative changes happened. The incidence is higher for all age groups in the periods before the legislative changes, which suggests that the decrease is not caused by lower reporting rates among people who are economically active, but is more likely a general trend.

To confirm this, we regress the incidence rates on a dummy indicating periods after the policy changes, quarters, and a polynomial time trend. The results in Table A2 show that the indicator for periods after the legislative changes does not explain the decrease in respiratory infections when controlling for the time trend and seasonality. This is true for all age groups. Therefore, we assume that the counts of reported acute respiratory infections are not endogenous to the legislative changes under consideration. We use two measures of local sickness levels in our analysis.

[13] More information on the ARI database can be found on the website of the National Institute of Public Health http://www.szu.cz/publikace/data/popis-systemu-ari?lang=1.

Apart from the normalized incidence of acute respiratory diseases (expressed as the number of influenza sickness spells per 100,000 people), we count the number of weeks with a flu epidemic status. The threshold for influenza epidemics is 1,800 normalized incidences.

3.2 EPIDAT

The EPIDAT data contain all reported cases of infectious diseases except acute respiratory diseases and HIV.[14] The database contains a detailed classification of a reported disease, the county of report, and information about a patient's gender and age group. We use quarterly data during 2005-2012. The coverage is similar to the ARI database, i.e., only reported sickness spells are included, which is supposed to be around one half of the total incidence in the population. Graph A2 (in the Appendix) shows the incidence evolution of selected groups of infectious diseases from the EPIDAT database.[15] Similarly to the respiratory infections, the data show clear seasonal patterns and the incidence is the highest for the youngest patients. Table A3 shows that the incidence of infectious diseases in the period after 2008 was higher for children and young people, lower for the elderly, and approximately the same for adults. The diagnosis groups with the highest incidence for adults, who are most likely to be economically active, are *Intestinal infectious disease*, *Viral disease affecting skin*, and *Other virus diseases*.

[14] A complete list of diseases and their classification can be found, e.g., at https://icd.who.int/browse10/2010/en#/I. More information about the database itself can be found here: http://www.szu.cz/publikace/data/infekce-v-cr?lang=1.

[15] In line with the official classification, we aggregate the infectious diseases into following groups: *"Other", "Intestinal infectious disease", "Other bacterial diseases", "Sexually transmitted diseases", "Other spirochetes bacterias", "Viruses affecting nervous system", "Viral disease affecting skin", "Viral hepatitis", "Other viral diseases", "Mykosis", "Helminthiasis", "Louses and similar"*. We omitted the groups of infectious diseases that included only a small number of observations.

3.3 SES

The Czech Structure of Earnings Survey (SES) allows us to observe the sickness-absence patterns of Czech employees. We use information on approximately 1.5 million private-sector employees from the Czech SES for each quarter during 2005-2012[16]. The data include repeated cross-section observations of all employed workers within surveyed firms. Firm-level data provide information about a firm's location (NUTS4 specification), 6-digit industry code, and the presence of a collective agreement. Data on employees contain: gender, age, place of work – county NUTS4 levels, hours worked, salary, occupation, education, tenure, and importantly, total hours absent, sickness-related absences, paid and unpaid leave.[17] Graph A3 shows a small decrease in *total hours absent* that was caused by a significant decrease in *sickness-related absences* and a small increase in *paid* and *unpaid leave* on average. The initial number of observations vary around 1.25 per quarter during the period studied. After dropping observations with missing values and keeping only full time workers we are left with approximately 95% of the original data.

3.4 Other data

We use several other data-sets in our analysis. First, we use information on the number of employees by age groups, gender, and industry who work under the shift-work regime. The data come from the "Work organization and working time

[16]More information about the Czech SES can be found on the web page `https://ispv.cz/en/homepage.aspx`.

[17]We use four types of hours absent collected in the Czech SES. The variable *total hours absent* reports the total number of hours absent in a quarter. *Paid leave* gives information on the total amount of hours absent for which an employee received a wage, e.g., vacations, state holidays, etc. *Unpaid leave* states the number of hours an employee officially took vacation but was not paid for this, i.e., it is vacation that is taken on the top of the settled amount. *sickness-related absences* include all hours absent when an employee reported himself ill; however, the variable does not distinguish the sickness of employees from absences that employees took to take care of sick relatives.

arrangements" survey compiled by Eurostat in 2004.[18] We implicitly assume that the structure of employees remained the same during subsequent years. Second, we use information on occupation-specific characteristics from the O*NET database.[19] Specifically, we use measures of how often (to what extent) specific occupations are exposed to other coworkers, disease spread, social interactions, etc., to determine which groups of workers are more likely to be exposed to sickness. Third, we use data from the Czech Statistical Office on the age profiles of parents, to assess whether an employee is a mother or father.

4 Empirical Design

We begin by establishing the relationship between hours absent and sickness rates. We approximate local sickness levels by the incidence of acute respiratory diseases and reported cases of infectious diseases.[20] We find positive correlations, conditional on seasonal and regional effects, between sickness-related absences and the incidence of acute respiratory infections in periods before and after the legislative changes were enacted (Table A4).[21] We argue that it is important to control for sickness rates when estimating the 'before-after' type of models, because it may affect the size of the estimated coefficients, e.g., the coefficient that is often reported as the effect of the policy reforms. Table A7 reports results when (not) controlling for the sickness rates in the estimated model.

We first estimate the effects of policy reforms using the 'before-after' estimation

[18]Description of the data can be found at https://ec.europa.eu/eurostat/cache/metadata/en/lfso_04_esms.htm.

[19]https://www.onetonline.org/

[20]Data-sets and the construction of variables used in our analysis are described in Section 3.

[21]We use a normalized incidence of acute respiratory infections and the number of weeks with influenza epidemic status in a quarter (1,800 cases per 100,000 employees and more) to measure local sickness levels. The data allow us to measure the sickness levels among children, adults, and the elderly. We prefer to use the counts of weeks with influenza epidemic status on the right hand side of the regression equations to avoid circular measurement.

strategy (the γ coefficient in Equation 1). This estimate is based on the comparison of two conditional means with little identification variation involved. Possibly, the estimate also captures the effects of events timed simultaneously with the policy reforms but otherwise unrelated. The estimate captures the overall effect of the policy reforms including absence adjustments for those who were shirking, suffered a disease, or were absent for another reason. Second, we use the prevalence of selected infectious diseases to provide variation in the need for sickness insurance. We use this variation to apply the *intensity treatment* identification strategy.[22] The intensity treatment here is the need for sickness insurance, which is high in counties with high sickness rates and is affected by the policy reforms; i.e., our estimation strategy relies on a quasi-random assignment to different levels of treatment. We focus on a narrow group of employees exposed to a specific disease, e.g., those who were exposed to influenza, and compare absences of employees differently exposed to influenza (i.e. with different needs for sickness insurance because of influenza) in the periods before and after the policy changes. In this framework, the policy changes did not affect the need for sickness insurance among those who were shirking or suffered from diseases other than influenza. The advantage of this strategy is that our estimates are based on much more variation than a simple 'before-after' comparison.[23] Our local average treatment estimates are important because they show how the policy reforms affected the spread of the disease in the workplace. Canceling sickness benefits during the first three days of sickness could incentivize employees to go to work sick, where they may infect other coworkers. The underlying identifying assumptions are that influenza outbreaks were not a consequence of sickness transmission in the workplace (it can make the situation worse but does not initiate the outbreaks) and that shirking is not affected by the epidemic situa-

[22]By construction, the *intensity treatment* is similar to the *difference-in-differences* estimator (for earlier applications see, e.g., Card, 1992; Machin et al., 2003).

[23]We use information about sickness incidence in 76 Czech counties. For more details, see section 3.

tion, i.e, employees do not shirk more during an outbreak. Given that we observe complete absence records of each employee decomposed by the type of absences (*sickness-related absences*, *paid* and *unpaid leave*), we bring qualitative evidence on the mechanism behind policy reforms and influenza outbreaks. This allows us to explain why the changes in hours absent happened in such a manner, and why these changes differ across selected socio-demographic groups of employees. We estimate the following equation.

$$\text{absence hours}_{c,i,t} = \alpha + \beta \text{ sickness}_{c,t} + \gamma \text{ after} + \delta \text{ sickness}_{c,t} * \text{after} + \eta \text{ X}_{c,i,t} + \epsilon_{c,i,t} \quad (1)$$

where the term *absence hours* denotes various types of hours absent, *sickness* represents measures of sickness incidence (normalized numbers and no. of weeks with epidemic status in counties; see Section 3 for more details). A possible concern would be that adult sickness rates (or total incidence in population) are endogenous to absences.[24] To address this issue, we use the measure of local influenza outbreaks among children, implicitly assuming that they can infect adults but not vice versa. We prefer to use the counts of weeks with epidemic status, i.e., we identify the effects using the variation that is based on whether or not the incidence of infections was significant during a specific week in a county. The corresponding threshold is the official definition of an infection outbreak - epidemic; for influenza it corresponds to 1,800 reported cases per 100,000 inhabitants. The announcement of epidemic status is not solely a formal declaration, but it allows government to use specific measures to fight the fast spreading disease (see Government decree no. 258/2000

[24]There might be another problem with using the normalized incidence measure among adults. If sick employees go to work, spread the flu among coworkers, and eventually report themselves sick, there would be one-to-one matching between local sickness-related absences and officially reported sickness incidences.

Sb.)[25]. Thus, our identification strategy assumes that the threshold for epidemic status correctly assesses the seriousness of the then current epidemic situation.

The variable *after* is an indicator for periods after the legislative changes, and hence the γ coefficient captures an effect of periods after the legislative changes were introduced (irrespective of our sickness exposure measures and other controls), X stands for other control variables, and ϵ are cluster-robust standard errors. Subscript c stands for county, i individuals, t time. The coefficient β shows how *sickness* affects hours absent in periods before the policy changes. We expect this coefficient to be positive for sickness absence hours as employees most likely stay home when they are sick (the adults' sickness measure) or they have to take care of their sick children (the sickness incidence among children; which also captures a possibility that children infect their parents). Unfortunately, the nature of the data does not allow us to distinguish whether an employee is sick or taking care of his/her sick children. It is less clear what sign to expect in the case of paid and unpaid hours absent; our expectation is that both coefficients have negative signs as employees take less vacation when sick/taking care of their sick children. The δ coefficient represents the adjustment/change in absences for employees in locations with incidence of sickness caused by the policy changes. Given that the β and δ coefficients capture the effect at the county-quarter level, a positive sign for the δ coefficient in the equation with the sickness-related absences as dependent variables would mean that the policy changes contributed to the spread of the disease among coworkers. In that case, the policy changes would cause negative externalities in the form of moral hazard, which may be financially more damaging than spending more on sickness benefits.

[25]For example, the Government can put restrictions on production, transport, distribution of food etc.

5 Results

We begin our analysis by establishing the relationship between our sickness measures and hours absent. Table A4 shows that there is a statistically significant relationship between normalized sickness-related absences and exposure to sickness, i.e., employees take more sick-leave during the flu season. Table A5 shows strong positive correlations between the normalized incidence of respiratory diseases and our exposure measure, defined as the number of weeks with influenza epidemic status per quarter. We further explore the relationship between sickness and absence rates on the level of occupations (for details see Table A6 in the Appendix). It could be that employees in some occupations take more sickness-related absences after exposure to influenza, e.g., they are more likely to get infected. In particular, we find persistent patterns of positive correlations among *Technicians and associate professionals* and *Clerical support workers* in the periods before and after 2008.

Baseline results

We continue by exploring how hours absent vary by differing exposure to sickness. We estimate Equation 1 using both measures of local sickness levels, i.e., the normalized incidence of acute respiratory diseases and the number of weeks with influenza epidemic status in a county per quarter. Our main results are presented in Table 2. The first three columns show results for when we employ the influenza outbreak among adults, the last three show results when the children' outbreak is employed. Both sets of estimated coefficients are similar in their signs.

For simplicity, we discuss our results below in terms of days absent for employees who were exposed to sickness, i.e., we interpret the effects for those who were sick.[26] We first focus on the results where we use the outbreak among adults.

[26] We recalculate the average effects (the β and δ coefficients) to the proportion of employees who were actually sick. The definition of influenza outbreak is 1,800 infected per 100,000 inhab-

Table 2: Hours absent - Respiratory infections outbreak

	Adults' outbreak			Children's outbreak		
	Sickness absences	Paid leave	Unpaid leave	Sickness absences	Paid leave	Unpaid leave
After	-9.003***	7.416***	2.243***	-7.726***	3.948***	-0.684
	(0.280)	(1.007)	(0.482)	(0.295)	(1.020)	(0.661)
Sickness	0.719***	-0.0574	-0.292**	0.148***	-0.259***	-0.228***
	(0.0629)	(0.142)	(0.124)	(0.0106)	(0.0405)	(0.0301)
After*Sickness	-0.961***	0.232	0.337	-0.176***	0.331***	0.302***
	(0.270)	(0.620)	(0.238)	(0.0112)	(0.0316)	(0.0256)
Observations	15,327,196	15,326,330	15,318,628	15,327,196	15,326,330	15,318,628
Adjusted R2	0.031	0.299	0.355	0.031	0.300	0.356

Notes: The table shows two sets of regression results (Equation 1). We use counts of weeks with epidemic in a quarter for adults in the first three columns, and for children in the last three columns. Dependent variables are: sickness-related absences (sickness absences), paid leave, and unpaid leave. Controls were: age, tenure, gender, collective agreement, quarter, year, county, industry, occupation, firm size cat., educ. cat., nationality and constant term. Cluster-robust errors in parentheses. Significance levels: *** 0.01, ** 0.05, * 0.1.

sickness-related absences are positively related to sickness incidence (coefficient β from Equation 1). Back-of-the-envelope calculations reveal that one extra week of epidemic status causes an increase in sickness-related absences of 5 working days. This is in line with the fact that flu symptoms last from 5 to 7 days.[27] Therefore, it appears that employees do not take advantage of influenza outbreaks to shirk; however, we cannot rule this out completely as some employees may go to work when sick and a similar number stay home during flu season when they are healthy. The opposite relationship holds for *unpaid leave*, where one week of influenza epidemics causes a 2-day decrease in hours absent, which means that employees took less unpaid leave when there was a higher incidence of influenza. Employees might not need to use unpaid leave when they are sick at home. The coefficients δ show

itants, i.e., we multiply the estimated coefficients by 100,000/1,800 to obtain hours absent, and further divide by 8, assuming that an average working day has 8 working hours. We use the same calculation procedure consistently throughout.

[27]For example, see https://www.health.harvard.edu/staying-healthy/how-long-does-the-flu-last.

how the relationship between hours absent and the influenza outbreak changed after the legislative changes were introduced. We find that an extra week of influenza epidemic decreased *sickness-related absences* (by 6.7 days), resulting in the overall effect of the influenza outbreak being negative (-1.7 days) in the periods after 2008. However, the legislative changes also caused increases in *paid* (1.6 days) and *unpaid leave* (2.3 days) compared to the situation before 2008, making the overall effect of an influenza outbreak on *paid* and *unpaid leave* positive in the periods after 2008 (1.5 days in total).[28] Our results indicate that the legislative changes led employees to almost perfectly substitute *sickness-related absences* by *paid* and *unpaid leave* when exposed to influenza outbreaks.

We observe a similar pattern when we employ the influenza outbreak among children measure (the last three columns of Table 2). The estimated β coefficients suggest that one extra week of influenza outbreak causes an increase in *sickness-related absences* of 1 day, which is a significantly lower effect compared to the estimate when the influenza outbreak among adults is employed.[29] It could be that employees are either sick because their children infected them (not every child infects its parents) or because they have to take care of their sick children (and they can share the responsibility to stay home within the family). However, they do not need to take as many *sickness-related absences* as for the adults' outbreak. Our findings further suggest that one extra week of influenza outbreak decreases *paid absence hours* by 1.8 days (employees spend less time on vacation when they or their children are sick) and *unpaid leave* by 1.6 days (they do not need to take extra unpaid leave when they are home sick or babysitting their children). Similarly to the results for the adults' outbreak, the δ coefficients indicate that the legislative changes caused a decrease in *sickness-related absences* by 1.2 days and an increase in *paid* (2.3 days)

[28] However, the δ coefficients for paid and unpaid leave are imprecisely estimated.

[29] The coefficients could be smaller because the sickness-related absences and adults' sickness rates are endogenous, there is a measurement error that produces downward bias, or a combination of both.

and *unpaid leave* (2.1 days) compared to the situation before 2008. The composite effects in periods after 2008 are that one extra week of influenza outbreak among children causes a small decrease in *sickness-related absences* (0.2 days) and a small increase in *paid* and *unpaid leave* (1 day). Overall, our results show that the legislative changes induced significant adjustments in employees' absences. However, though the substitution effects among types of hours absent are substantial, the overall effect on total hours absent is small.

Table A8 shows similar results to Table 2, where the normalized measure of influenza incidence is used on the right hand side of the regression equations. Both sets of results are similar in terms of their sign and size. We observe that *sickness-related absences* are positively related to sickness levels (one st.dev. increase in sickness exposure causes an increase of 1.03 hours). The opposite relationship holds for *paid leave* (one st.dev. increase in sickness exposure causes a decrease of 1.48 hours) and *unpaid leave* (one st.dev. increase in sickness exposure causes a decrease of 0.76 hours). A one standard deviation increase in sickness incidence after the legislative changes were introduced (i.e., the coefficient *delta*) would cause *sickness-related absences* to decrease by 1.01 hours, *paid leave* to increase by 1.82 hours, and *unpaid leave* by 1.53 hours. Similarly to our previous results, this pattern indicates that employees substituted *sickness-related absences* with *paid* and *unpaid leave.*

We complement our main results by studying the effects of other "non-respiratory" infectious diseases on hours absent. Specifically, we use the normalized incidence of selected infectious diseases except acute respiratory diseases and HIV among children from the EPIDAT data-set and estimate Equation 1.[30] The results are in Table A9. For many diagnosis groups, we find similar substitution effects to those our main results. However, all these effects are small and have almost no economic impact (the effects of the highest magnitude vary around 1 hour of absence). Therefore, in

[30]We use only selected groups of diseases with sufficient numbers of local incidence and variation. The data from the EPIDAT data-set are described in Section 3.

the following text we continue with our analysis of exposure to influenza.

Heterogenous effects

We extend our baseline analysis by identifying groups of employees who may have different reasons for being absent, for example because they have to stay with sick children at home, are frequently in contact with other people that may infect them, or their work conditions make their absence more costly. Specifically, we estimate the effects for likely mothers and fathers separately, identify the occupations with high shares of employees working in the shift-work regime, and use the O*NET database to select employees with i) a high probability of a disease spread, ii) frequent contact with other coworkers, and iii) high social interactions. In each case we split our sample and compare whether the estimated coefficients from Equation 1 differ for observations with high/low values. For each chosen characteristic, we divide the observations into quartiles and present the results (Tables A11, A12, A13, A14) for all observations in the first three columns, those in the top quartile (columns 4-6), and these up to the 75th percentile (columns 7-9) separately.

First, we assess whether an employee is likely to be a mother or father. Since our data do not include information about the number of employees' children, we approximate that every female between 23-44 years old is likely to be a mother and every male between 26-47 is likely to be a father. Our assessment is based on the age profile of parents in the Czech Republic.[31] The estimates from Equation 1, with the adults' sickness exposure in Table 3 for mothers and Table A10 for fathers, show that

[31] The fertility distribution among Czech women shows that the most common age to give birth is between 23-33 years (the mean age is 29 years). We use 2005 data assuming that women stay home with a child for 3 years, so the data correspond to the timing of the policy changes that happened during 2008-2009. Therefore, given that children's needs are most time-consuming up to the age of 11 (Milkie et al., 2015), we approximate that a woman is a mother of a young child who needs to be taken care of when she is 23-44. Similarly, we define fathers as on average, 3 years older, i.e. we say that a man is father if he is 26-47 years old. Source https://www.czso.cz/csu/xb/vek-rodicu-v-jihomoravskem-kraji-v-roce-2017.

coefficients β and δ are not statistically different from the estimated population-wide effects, nor do they differ across the subsamples of mothers and fathers. However, there are statistically significant differences in the case of influenza outbreaks among children. Mothers had more sickness-related absences during influenza outbreaks before 2008 (the β coefficient). It is likely that they spent more time at home with their sick children than their partners. The decrease in sickness-related absences caused by legislative changes (the δ coefficient) is statistically larger for mothers, who adjusted their behavior more. Our results suggest that fathers partially compensated for this by increasing paid leave (the coefficient δ in Table A10).[32]

Table 3: Subsample of mothers - Influenza outbreak

	Adults' outbreak			Children'n outbreak		
	Sickness absences	Paid leave	Unpaid leave	Sickness absences	Paid leave	Unpaid leave
After	-11.05***	6.775***	1.475***	-9.364***	3.794***	-1.188***
	(0.439)	(0.763)	(0.349)	(0.443)	(0.760)	(0.410)
Sickness	0.873***	-0.259*	-0.508***	0.205***	-0.274***	-0.237***
	(0.0927)	(0.136)	(0.118)	(0.0154)	(0.0340)	(0.0255)
After*Sickness	-1.080***	0.0731	0.679***	-0.224***	0.291***	0.293***
	(0.207)	(0.595)	(0.225)	(0.0151)	(0.0290)	(0.0184)
Observations	3,292,272	3,292,206	3,290,553	3,292,272	3,292,206	3,290,553
Adjusted R2	0.033	0.347	0.409	0.033	0.348	0.411

Notes: The table shows two sets of regression results (Equation 1) for the subsample of mothers(females 23-44 y.o.). We use counts of weeks with epidemics in a quarter for adults in the first three columns, and for children in the last three columns. Dependent variables are sickness-related absences (sickness absences), paid leave, and unpaid leave. Controls included are age, tenure, gender, collective agreement, quarter, year, county, industry, occupation, firm size cat., educ. cat., nationality and constant term. Cluster-robust errors in parentheses. Significance levels: *** 0.01, ** 0.05, * 0.1.

Second, we use two-digit-occupation-specific information on the share of employ-

[32] Our findings suggest that prior to 2008, it was mothers who stayed home with their sick children. This could implicitly disadvantage them (it is likely that they will have more absences compared to their male coworkers) and contribute to a larger gender-wage gap. The situation improved when fathers started to take care of sick children more after 2008, which could steer perceived differences and make the situation more equal, but not completely.

ees who work under the shift-work regime (for details see Section 3). We assume that shift-work employees have fewer opportunities to shirk, since the production is heavily dependent on their presence at the workplace, and thus employers do not tolerate unjustified absences. Table A11 shows that there are small differences between occupations with "high" and "low" shares of shift-work employees but the substitution pattern is similar to our main results. We find that employees in the "high" occupations classification show a slightly larger β estimate in the *sickness-related absences* regression and smaller estimates (half the size) in absolute values for *paid* and *unpaid leave*.[33] This indicates that employees in occupations with high shares of shift-workers took more sick leave, but also took more paid and unpaid leave than the rest of the sample during flu outbreaks. The estimated δ coefficients are significantly lower for *paid* and *unpaid absence hours* among occupations with high shares of employees working shifts, which suggests that the substitution effect of the legislative changes was much lower for these occupations. This is in line with our expectation that shift-working employees have less flexibility.

Third, we use the O*NET database to classify occupations based on how much they are exposed to diseases or infections, how intensive their contact with others is, and how socially oriented their occupation.[34] We expect a stronger reaction to influenza outbreaks among occupations with high scores.[35] Similarly to previous classifications, we divide observations into quartiles based on the above defined O*NET scores and estimate Equation 1 for all observations, for the top quartile, and

[33]The regressions control for occupation fixed effects.

[34]The classification is carried out based on the following exact formulations. Exposed to Disease or Infections: *"How often does this job require exposure to disease/infections?"*, Contact With Others: *"How much does this job require the worker to be in contact with others (face-to-face, by telephone, or otherwise) in order to perform it?"*, Social Orientation: *"Job requires preferring to work with others rather than alone, and being personally connected with others on the job"*. Each occupation is assessed on a scale from 0 (minimum) to 100 (maximum).

[35]We expect that influenza spreads with higher intensity in occupations that are more exposed to disease or infections, (employees are more likely to be exposed to disease), with more intense contact with others (employees are more likely to meet someone who is infectious), and in more "pro-social" occupations (more frequent interaction with people is associated with a higher probability catching a disease from someone who is infectious).

those that belong to the first three quartiles. The results are presented in Tables A12, A13, and A14. We find that the estimated coefficients for subsamples based on all three classifications yield similar results. Similarly to our baseline results, there are positive effects of influenza outbreaks on *sickness-related absences* and negative effects on *paid* and *unpaid leave* in the periods before 2008. The legislative changes (δ estimates) caused the opposite effects, i.e., employees substituted *sickness-related absences* by *paid* and *unpaid leave*. However, the sizes of estimated coefficients differ for employees who belong to the highest quartiles, based on our classifications. On average, we observe a higher decrease in *sickness-related absences* and a smaller increase in *paid* and *unpaid absence hours* in the periods after 2009 (the γ coefficients). Those employees also took more *sickness-related absences* and more *paid* and *unpaid absence hours* compared to the rest of the sample when exposed to influenza outbreaks prior to 2008. We further observe that their *sickness-related absences* decrease more and *paid* and *unpaid leave* increase less as a reaction to the enacted legislative changes (the δ estimates from Equation 1). The results suggest that the substitution effect for the "high" group was not as large as for the rest of the employees.

Finally, we ask whether absence behavior differs by the size of job cells. These are firm-county-occupation specific organizational units with employees who have similar characteristics and, thus similar absence behavior (for determinants of absence behavior see, e.g., Barmby, 2002; Scoppa, 2010).[36] The larger the job cell is, the more likely is that sick employees infect more of their coworkers. We employ the regression equation similar to Equation 1 but we estimate it on the level of job cells. The dependent variables are the average absence hours in the job cell and the independent variables of interest are mutual interactions of a dummy indicating periods after the change, job-cell size (the natural logarithm of number of employees in a

[36] We prefer to use job cells to firms because employees in the same occupations, tend to meet each others more frequently within a firm e.g., manual assembly workers vs. managers.

job cell), and our sickness measures. We use standard control variables and include the job-cell fixed effects to control for unobserved differences between organizational units.

The results from the first two rows in Table A15 are similar to our β and δ baseline estimates and follow the story that employees substitute sickness-related absences by paid and unpaid leave. The positive coefficient associated with the interaction term of the sickness measure and job-cell size shows that employees of larger job cells took more sickness-related absences when exposed to influenza outbreaks.[37] This suggests that employees spread the flu at work in both periods before and after the legislative changes to a similar extent, which is natural as they interact. However, we do not find evidence that the legislative changes had either a positive or negative effect on the spread of disease at the workplace (the triple interaction term in Table A15). If the reforms caused more intense disease spread, we would observe coefficients with positive signs.

6 Conclusion

This paper studies the effects of decreases in sickness benefits during 2008/9 in the Czech Republic on hours absent from work of private sector employees. We use local exposure to sickness -influenza outbreaks to provide variation in the need for sickness insurance, which allows us to apply an intensity treatment estimator on the county level. Compared to the 'before-after' approach, our local average treatment estimates are more conducive to causal interpretation. Assuming that adults' sickness rates and absences from work may be endogenous, we use children's sickness rates to measure the exposure to sickness. Our results suggest that as a reaction to the decrease in sickness benefits, employees exposed to influenza outbreaks re-

[37] The effect of the outbreak among adults on sickness-related absences is imprecisely estimated.

duced their sickness-related absences but almost perfectly compensated this drop by taking paid and unpaid leave, leaving total absences at the same level. Hence it is unlikely that the reforms led to more employees working while sick. We do not find evidence that employees spread influenza among their coworkers more in periods when sickness benefits were reduced or that employees took advantage of influenza outbreaks to shirk; although we cannot rule this out completely. The size of the substitution effect differs by occupational and sociodemographic characteristics of employees. Mothers, who took more sickness-related absences before the policy changes (probably as a result of taking care of their sick children), took less sickness-related absences than other employees. Fathers compensated for this reduction in sickness-related absences taken by mothers by increasing their paid and unpaid leave. We find a smaller substitution effect for employees who work in occupations that are more exposed to diseases or where social interaction is more frequent.

References

F. D. Amuri. Monitoring , monetary incentives and workers ' rents in determining absenteeism. 2011.

T. Barmby. Worker absenteeism: A discrete hazard model with bivariate heterogeneity. *Labour Economics*, 9(4):469–476, 2002. ISSN 09275371. doi: 10.1016/S0927-5371(02)00042-8.

D. Card. Using regional variation in wages to measure the effects of the federal minimum wage. *Ilr Review*, 46(1):22–37, 1992.

T. C. Clayton, M. Thompson, and T. W. Meade. Recent respiratory infection and risk of cardiovascular disease: Case-control study through a general practice database. *European Heart Journal*, 29(1):96–103, 2008. ISSN 0195668X. doi: 10.1093/eurheartj/ehm516.

M. Csillag. THE INCENTIVE EFFECTS OF SICKNESS - ANALYSIS OF A " NATURAL EXPERIMENT ". Number 2016, pages 1–21, 2017.

M. De Paola. Absenteeism and peer interaction effects: Evidence from an Italian Public Institute. *Journal of Socio-Economics*, 39(3):420–428, 2010. ISSN 10535357. doi: 10.1016/j.socec.2010.02.004. URL http://dx.doi.org/10.1016/j.socec.2010.02.004.

M. De Paola, V. Scoppa, and V. Pupo. Absenteeism in the Italian Public Sector: The Effects of Changes in Sick Leave Policy. *Journal of Labor Economics*, 32(2): 337–360, 2014. ISSN 0734306X. doi: 10.1086/674986.

European Commission's DG for Employment Social Affairs & Inclusion. Employment, Social Affairs and Inclusion, 2017. URL http://ec.europa.eu/social/main.jsp?catId=815{&}langId=en.

M. A. Herrmann and J. E. Rockoff. DOES MENSTRUATION EXPLAIN GENDER GAPS IN WORK ABSENTEEISM? 2010.

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

S. Machin, A. Manning, and L. Rahman. Where the Minimum Wage Bites Hard: Introduction of Minimum Wages to a Low Wage Sector. *Journal of the European Economic Association*, 1(1):154–180, 2003. ISSN 1542-4766. doi: 10.1162/154247603322256792. URL https://academic.oup.com/jeea/article/2280926/Where.

M. A. Milkie, K. M. Nomaguchi, and K. E. Denny. Does the amount of time mothers spend with children or adolescents matter? *Journal of Marriage and Family*, 77 (2):355–372, 2015. ISSN 17413737. doi: 10.1111/jomf.12170.

Ministry of Labour and Social Affairs. Informace o vyplacených dávkách v resortu MPSV ČR v prosinci 2017. Technical report, Ministry of Labour and Social Affairs, 2017. URL https://www.mpsv.cz/files/clanky/32548/Informace{_}o{_}vyplacenych{_}davkach{_}v{_}prosinci{_}2017.pdf.

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

F. Pertold. What if they take it all? Heterogeneous impact of sickness absence reform. *Economics of Transition and Institutional Change*, 27(3):647–671, 2019. ISSN 2577-6975. doi: 10.1111/ecot.12201.

P. Pettersson-Lidbom and P. S. Thoursie. Temporary Disability Insurance and Labor Supply: Evidence from a Natural Experiment*. *Scandinavian Journal of*

Economics, 115(2):485–507, 2013. ISSN 03470520. doi: 10.1111/j.1467-9442.2012.01746.x.

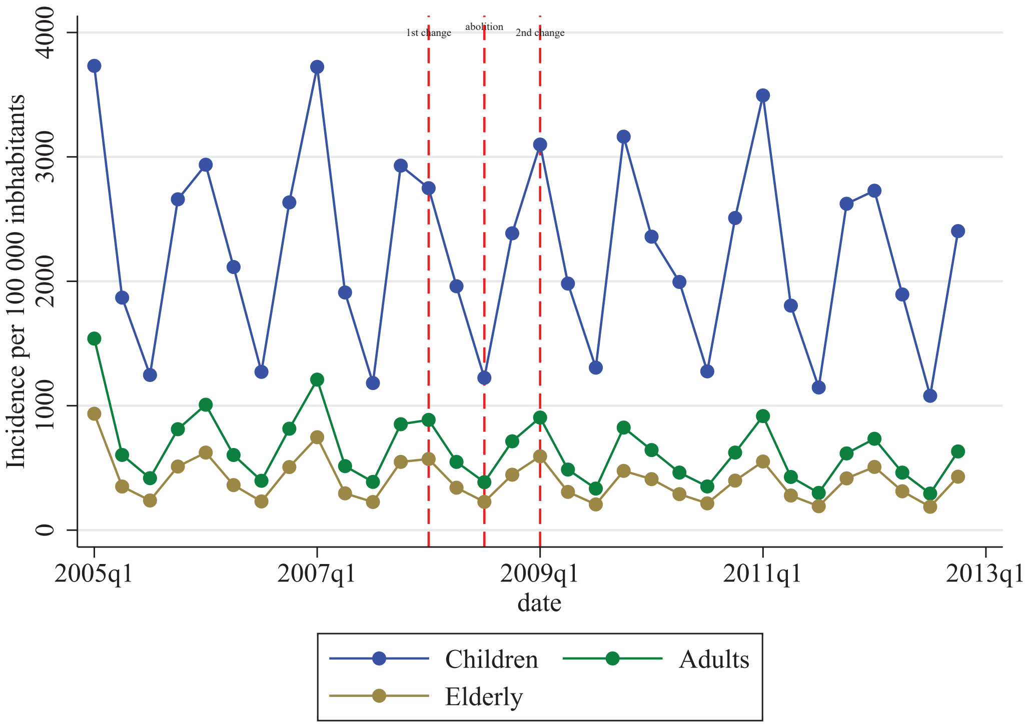
V. Scoppa. The influence of inertia on contract design: Contingency planning in information technology service contracts. *Managerial and Decision Economics*, 31(April):503–515, 2010. ISSN 1099-1468. doi: 10.1002/mde.

N. R. Ziebarth and M. Karlsson. A natural experiment on sick pay cuts, sickness absence, and labor costs. *Journal of Public Economics*, 94(11-12):1108–1122, 2010. ISSN 00472727. doi: 10.1016/j.jpubeco.2010.09.001. URL http://dx.doi.org/10.1016/j.jpubeco.2010.09.001.

A1 Appendix

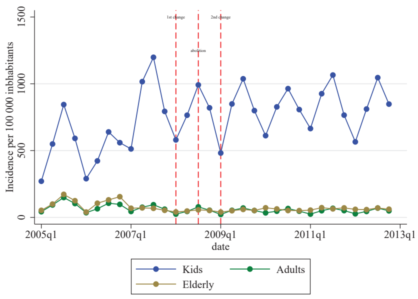
Graphs

Figure A1: Incidence of respiratory diseases by age groups (ARI database)

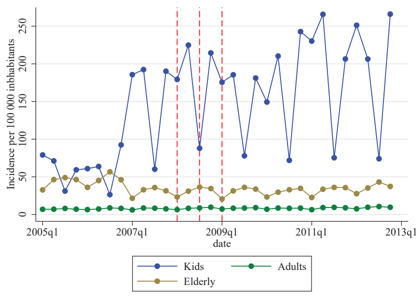


Note: Average incidence across 77 counties for age groups (0-14; 15-59; 60+) in the Czech Republic. The red bars indicate the timing of the legislative changes in sick-pay policy. The red vertical lines indicate the timing of the legislative changes.

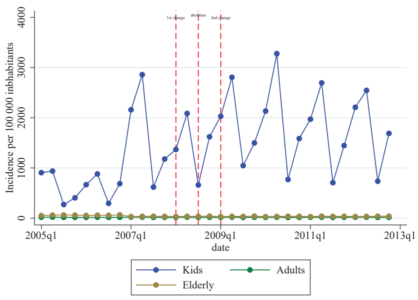
Figure A2: Incidence of selected groups of infectious diseases (EPIDAT database)



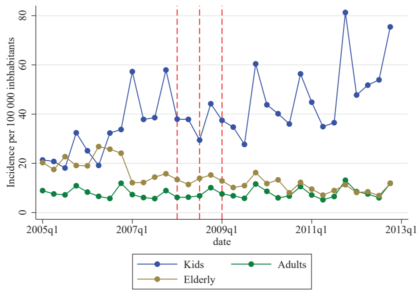
(a) Diagnosis group: Intestinal infectious diseases



(b) Diagnosis group: Other bacterial diseases



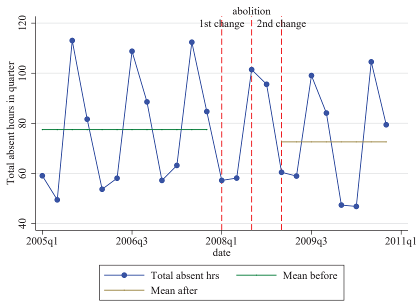
(c) Diagnosis group: Viral diseases affecting skin



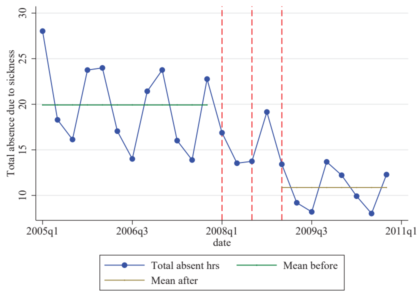
(d) Diagnosis group: Louses and similar

Note: The graphs show the incidence of selected infectious diseases from the EPIDAT database. The red vertical lines indicate the timing of the legislative changes.

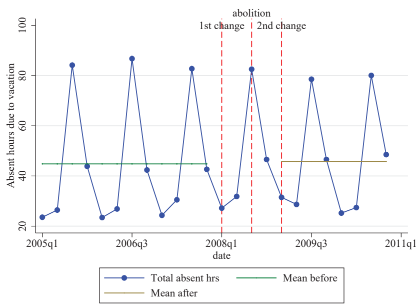
Figure A3: Hours absent before and after the reform



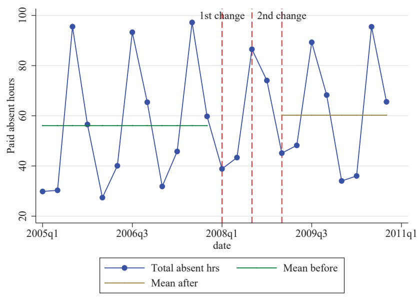
(a) Total hours absent



(b) Sickness-related absences



(c) Paid leave (hrs)



(d) Unpaid leave (hrs)

Note: The graphs show average quartal hours absent (by category) with the means for periods before and after the reforms. The red vertical lines indicate the timing of the legislative changes.

Tables - Descriptive

Table A1: Comparison of acute respiratory diseases by age groups, before and after the policy changes

	Children			Adults			Elderly			Total		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
After reform	-171.9***	320.8***	18.90	-199.9***	134.4***	11.27	-103.9***	72.92***	-5.477	-204.5***	163.6***	8.386
	(42.89)	(43.41)	(42.45)	(13.18)	(18.76)	(17.76)	(12.97)	(13.82)	(13.23)	(16.22)	(19.11)	(17.84)
Constant	2350.9***	2534.2***	3252.6***	763.4***	971.7***	1233.8***	464.7***	586.9***	756.1***	1102.6***	1311.7***	1664.1***
	(70.58)	(64.79)	(72.08)	(19.49)	(25.46)	(29.59)	(20.32)	(24.72)	(31.43)	(26.33)	(28.73)	(32.50)
Time trend	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Quartal	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Observations	2492	2492	2492	2492	2492	2492	2492	2492	2492	2492	2492	2492
Adjusted R^2	0.006	0.017	0.509	0.084	0.129	0.603	0.035	0.056	0.369	0.049	0.078	0.619

Notes: Average incidence of acute respiratory diseases per 100,000 inhabitants across 77 counties by age groups. Standard deviations in italics.

Table A2: Incidence of acute respiratory diseases

	Children			Adults			Elderly			Total		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
After reform	-171.9***	320.8***	18.90	-199.9***	134.4***	11.27	-103.9***	72.92***	-5.477	-204.5***	163.6***	8.386
	(42.89)	(43.41)	(42.45)	(13.18)	(18.76)	(17.76)	(12.97)	(13.82)	(13.23)	(16.22)	(19.11)	(17.84)
Constant	2350.9***	2534.2***	3252.6***	763.4***	971.7***	1233.8***	464.7***	586.9***	756.1***	1102.6***	1311.7***	1664.1***
	(70.58)	(64.79)	(72.08)	(19.49)	(25.46)	(29.59)	(20.32)	(24.72)	(31.43)	(26.33)	(28.73)	(32.50)
Time trend	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Quartal	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Observations	2492	2492	2492	2492	2492	2492	2492	2492	2492	2492	2492	2492
Adjusted R^2	0.006	0.017	0.509	0.084	0.129	0.603	0.035	0.056	0.369	0.049	0.078	0.619

Notes: We regress a county level incidence of acute respiratory infections on a dummy variable indicating periods after the policy change, conditional on polynomial time trends and indicators of quarters. We use clustered errors on the county level. Significance levels: *** 0.01, ** 0.05, * 0.1. Standard errors in parenthesis.

Table A3: Comparison of infectious diseases by age groups before and after the legislative changes

		before 2008				after 2009			
		kids	adults	elderly	total	kids	adults	elderly	total
	Diagnosis group								
0	Other	9.8	2.8	6.1	2.4	15.2	2.6	3.9	2.2
		6.3	*2.2*	*4.3*	*1.9*	*9.9*	*2.2*	*2.3*	*1.8*
1	Intestinal infectious disease	639.9	80.6	95.4	145.3	817.0	48.4	59.3	102.5
		398.3	*48.0*	*84.9*	*76.4*	*407.5*	*30.2*	*55.5*	*49.2*
2	Other bacterial diseases	93.9	7.5	40.0	20.3	181.1	8.6	32.2	25.1
		107.6	*5.3*	*34.4*	*12.8*	*160.0*	*6.5*	*26.6*	*15.4*
3	Sexually transmitted diseases	5.8	5.9	5.0	4.2	15.8	7.5	4.4	5.2
		2.8	*9.5*	*4.1*	*6.7*	*7.0*	*8.6*	*3.3*	*6.1*
4	Other spirochetes bacterias	21.7	10.1	22.8	11.0	38.8	10.5	16.5	11.7
		20.2	*13.8*	*31.3*	*14.9*	*35.9*	*12.9*	*19.8*	*14.4*
5	Viruses affecting nervous system	19.2	5.1	10.2	5.2	23.4	4.7	6.6	4.4
		23.3	*5.3*	*11.4*	*5.7*	*18.8*	*4.7*	*6.6*	*4.5*
6	Viral disease affecting skin	990.1	17.7	51.3	125.5	1822.8	17.2	35.6	143.3
		1148.7	*10.7*	*35.3*	*104.7*	*1610.9*	*10.7*	*23.5*	*114.0*
7	Viral hepatitis	19.2	5.7	6.8	4.6	62.1	5.9	4.5	5.1
		35.2	*7.2*	*5.3*	*6.0*	*106.9*	*6.8*	*3.1*	*7.1*
8	Other viral diseases	44.2	11.4	8.3	11.9	70.9	11.1	3.9	11.3
		65.8	*16.5*	*11.1*	*16.5*	*141.1*	*26.6*	*2.4*	*24.7*
9	Mykosis	12.4	6.1	20.8	5.7	23.9	6.0	11.3	5.5
		9.8	*7.0*	*20.8*	*7.3*	*19.6*	*6.3*	*9.3*	*6.4*
10	Helminthiasis	24.3	1.8	6.0	3.2	30.9	1.6	3.2	2.4
		21.8	*1.4*	*3.6*	*2.8*	*25.6*	*1.0*	*1.7*	*1.9*
11	Louses and similar	32.9	8.0	19.0	10.3	49.3	8.2	10.7	9.2
		39.0	*8.2*	*25.2*	*10.2*	*55.0*	*9.1*	*12.0*	*9.9*

Note: Average incidence of infectious diseases per 100,000 inhabitants across 77 counties by age groups. Standard deviations in italics.

Tables - Results

Table A4: Hours absent and respiratory infections correlations

	Before			After		
	Total	Children	Adults	Total	Children	Adults
Normalized sickness	0.00133**	0.00007	0.00397***	0.00101***	0.000101	0.00254***
Sickness outbreak	0.241***	0.102***	0.705***	-0.168***	-0.0556***	-0.392*
Observations	9,385,668	9,385,668	9,385,668	7,660,028	7,660,028	7,660,028

Notes: The table presents correlations between sickness-related absences and county-level exposure to influenza-like diseases in periods before and after the legislative changes were enacted. Correlations are net of seasonal and regional effects. The first line counts the sickness exposure expressed as a normalized incidence of influenza. The second line shows results where the sickness exposure is measured as number of weeks with epidemics status. Standard age groups are used. Significance levels: *** 0.01, ** 0.05, * 0.1.

Table A5: Correlation matrix of influenza measures

		Normalized incidence			
		Children	Adults	Elderly	Total
Influenza outbr.	Children	0.8625*	0.6886*	0.4504*	0.8083*
	Adults	0.3013*	0.4688*	0.2854*	0.4062*
	Elderly	0.0904	0.0716	0.5901*	0.1349*
	Total	0.6882*	0.7228*	0.5401*	0.7461*

Notes: The table presents a correlation matrix for normalized incidence of influenza and the influenza outbreak measure computed as the number of weeks with influenza epidemic status per quarter. The correlations are shown for three age groups as well as aggregates. An observational unit is quarter-year-county specific. Standard age groups are used. Significance level: * 0.01

Table A6: Hours absent and respiratory infections correlations (by occupations)

Group	CZ ISCO	Occupation	Sickness exposure: Before, Children	Before, Adults	Before, Total	After, Children	After, Adults	After, Total
Professionals								
	21	Science and engineering professionals	0	0.00206***	0.00119***	0.000190**	0.00169***	0.000900***
			292,996	*292,996*	*292,996*	*310,888*	*310,888*	*310,888*
	23	Teaching professionals	0	0.00101**	0	0.000262**	0.00106*	0.000893**
			131,712	*131,712*	*131,712*	*115,572*	*115,572*	*115,572*
	24	Business and administration professionals	0	0.00316***	0.00147***	0	0.00316***	0.000936**
			413,076	*413,076*	*413,076*	*380,332*	*380,332*	*380,332*
Technicians and associate professionals								
	31	Science and engineering associate professionals	0.000231**	0.00252***	0.00134***	0.000299**	0.00285***	0.00139***
			904,060	*904,060*	*904,060*	*737,004*	*737,004*	*737,004*
	32	Health associate professionals	0.00127***	0.00236**	0.00373***	0	0	0
			127,976	*127,976*	*127,976*	*204,236*	*204,236*	*204,236*
	34	Legal, social, cultural and related associate professionals	0.000557***	0.00257***	0.00194***	0.000220*	0.00254***	0.00120***
			727,981	*727,981*	*727,981*	*634,021*	*634,021*	*634,021*
Clerical support workers								
	41	General and keyboard clerks	0.000983*	0.00458***	0.00357**	0.000329*	0.00385***	0.00175***
			514,144	*514,144*	*514,144*	*445,024*	*445,024*	*445,024*
	42	Customer services clerks	0.00134***	0.00625***	0.00523***	0	0.00457***	0.00225***
			319,064	*319,064*	*319,064*	*256,236*	*256,236*	*256,236*
Service and sales workers								
	51	Personal service workers	0.000723*	0.00456***	0.00336***	0	0.00302**	0
			251,712	*251,712*	*251,712*	*260,092*	*260,092*	*260,092*
	52	Sales workers	0.000876**	0.00457***	0.00392***	0	0.00323***	0.00157**
			230,688	*230,688*	*230,688*	*275,344*	*275,344*	*275,344*
Skilled agricultural, forestry and fishery workers								
	61	Market-oriented skilled agricultural workers	0	0.00657***	0.00486**	0.00135*	0	0.00508**
			73,248	*73,248*	*73,248*	*32,696*	*32,696*	*32,696*
Craft and related trades workers								
	71	Building and related trades workers, excluding electricians	0	0.00378**	0	0	0.00528***	0.00231**
			278,940	*278,940*	*278,940*	*228,740*	*228,740*	*228,740*
	72	Metal, machinery and related trades workers	0	0.00482***	0.00219**	0.000437**	0.00495***	0.00235***
			1,476,708	*1,476,708*	*1,476,708*	*1,013,580*	*1,013,580*	*1,013,580*
Plant and machine operators, and assemblers								
	81	Stationary plant and machine operators	0	0	0	0	0.00319**	0
			583,536	*583,536*	*583,536*	*400,828*	*400,828*	*400,828*
	82	Assemblers	0	0.00365***	0	0	0.00400***	0.00171*
			895,104	*895,104*	*895,104*	*639,996*	*639,996*	*639,996*
	83	Drivers and mobile plant operators	0.00103**	0.00510***	0.00392***	0	0.00424***	0.00180**
			697,768	*697,768*	*697,768*	*555,728*	*555,728*	*555,728*
Elementary occupations								
	91	Cleaners and helpers	0	0	0	0	0	0
			198,544	*198,544*	*198,544*	*145,008*	*145,008*	*145,008*
	92	Agricultural, forestry and fishery labourers	0	0	0	0	0	0
			5,240	*5,240*	*5,240*	*2,848*	*2,848*	*2,848*
	93	Labourers in mining, construction, manufacturing and transport	0	0.00290***	0	0.000716*	0.00369**	0.00250**
			338,324	*338,324*	*338,324*	*237,380*	*237,380*	*237,380*

Notes: The table shows correlations between sickness-related absences and county-level exposure to influenza-like diseases by chosen occupations. Correlations are net of seasonal and regional effects. The exposure to sickness is measured as a normalized incidence of influenza. The number of observations are in italics. For clarity, the insignificant correlations are in the table substituted by 0. Standard age groups are used. Significance levels: *** 0.01, ** 0.05, * 0.1.

Table A7: Sickness-related absence - controlling for sickness rates

	Controlling for sickness	Not controlling for sickness
After	-9.003***	-9.632***
	(0.280)	(0.271)
Observations	15,327,196	15,327,196
Adjusted R2	0.031	0.031

Notes: The table shows two regression results from Equation 1. The dependent variables are sickness-related absences. The results in the first column control for sickness exposure (influenza outbreak among adults) whilst the results in the second column control only for periods after the change. Other controls included: age, tenure, gender, collective agreement, quarter, year, county, industry, occupation, firm size cat., educ. cat., nationality. Cluster-robust standard errors in parentheses. Significance levels: *** 0.01, ** 0.05, * 0.1.

Table A8: Hours Absent - Respiratory infections exposure

	Adults' exposure			Children's exposure		
	Sickness absences	Paid leave	Unpaid leave	Sickness absences	Paid leave	Unpaid leave
After	-4.813***	-0.0771	-3.080***	-6.901***	2.729**	-1.271*
	(0.343)	(1.666)	(0.867)	(0.400)	(1.227)	(0.750)
Sickness	0.00570***	-0.00276***	-0.00253***	0.000967***	-0.00138***	-0.000713***
	(0.000296)	(0.000940)	(0.000633)	(0.0000979)	(0.000379)	(0.000203)
After*Sickness	-0.00606***	0.0135***	0.00964***	-0.00106***	0.00190***	0.00159***
	(0.000470)	(0.00152)	(0.000945)	(0.000140)	(0.000270)	(0.000190)
Observations	15,327,196	15,326,330	15,318,628	15,327,196	15,326,330	15,318,628
Adjusted R2	0.031	0.301	0.357	0.031	0.300	0.356

Notes: The table shows two sets of regression results (Equation 1). We use normalized adult sickness rates in the first three columns and normalized children's sickness rates in the last three columns. The dependent variables are: total absences, sickness-related absences, paid and unpaid leave. Controls include: age, tenure, gender, collective agreement, quarter, year, county, industry, occupation, firm size cat., educ. cat., nationality. Cluster-robust standard errors in parentheses. Significance levels: *** 0.01, ** 0.05, * 0.1.

Table A9: Hours absent - Infectious diseases other than respiratory (EPIDAT)

	Sickness absences	Paid leave	Unpaid leave
After	-9.269***	9.515***	4.237***
	(0.349)	(1.447)	(0.644)
Group 1	-0.00275***	0.00371***	0.00121**
	(0.000245)	(0.000944)	(0.000511)
After * Group 1	0.00127***	-0.00566***	-0.00466***
	(0.000307)	(0.000809)	(0.000485)
Group 2	0.00285***	-0.00330**	-0.00253**
	(0.000650)	(0.00148)	(0.00123)
After * Group 2	-0.00350***	0.00816***	0.00945***
	(0.000760)	(0.00216)	(0.00129)
Group 6	0.000132**	0.000404**	0.000379***
	(0.0000550)	(0.000169)	(0.000115)
After * Group 6	-0.000200***	-0.000198	-0.000260**
	(0.0000609)	(0.000214)	(0.000131)
Group 11	0.0103***	-0.0186**	-0.0104*
	(0.00200)	(0.00913)	(0.00592)
After * Group 11	-0.0162***	0.0285***	0.0233***
	(0.00256)	(0.00833)	(0.00526)
Observations	15,327,196	15,326,330	15,318,628
Adjusted R^2	0.031	0.300	0.356

Notes: The table shows regression results from Equation 1. We use the normalized incidence of selected infectious diseases from the EPIDAT database as defined in 3 (Group 1: *Intestinal infectious diseases*; Group 2: *Other bacterial diseases*; Group 6: *Viral diseases affecting skin*; Group 11: *Louses and similar*). The dependent variables are: sickness-related absences, paid and unpaid leave. Controls include: age, tenure, gender, collective agreement, quarter, year, county, industry, occupation, firm size cat., educ. cat., nationality and constant term. Cluster-robust errors in parentheses. Significance levels: *** 0.01, ** 0.05, * 0.1.

Table A10: Subsample of Fathers - Influenza outbreak

	Adults' outbreak			Children's outbreak		
	Sickness absences	Paid leave	Unpaid leave	Sickness absences	Paid leave	Unpaid leave
After	-7.383***	6.996***	2.310***	-6.488***	3.131**	-0.940
	(0.293)	(1.346)	(0.534)	(0.321)	(1.285)	(0.754)
Sickness	0.814***	-0.0815	-0.282*	0.126***	-0.286***	-0.263***
	(0.0793)	(0.164)	(0.145)	(0.0113)	(0.0462)	(0.0326)
After*Sickness	-1.030***	0.448	0.182	-0.148***	0.368***	0.322***
	(0.333)	(0.591)	(0.271)	(0.0118)	(0.0385)	(0.0305)
Observations	5,329,632	5,329,325	5,327,098	5,329,632	5,329,325	5,327,098
Adjusted R2	0.031	0.268	0.330	0.031	0.270	0.331

Notes: The table shows two sets of regression results (Equation 1) for the fathers' subsample (males 26-47 y.o.). We use counts of weeks with epidemics in a quarter for adults in the first three columns and for children in the last three columns. The dependent variables are: sickness-related absences, paid leave, and unpaid leave. Controls include: age, tenure, gender, collective agreement, quarter, year, county, industry, occupation, firm size cat., educ. cat., nationality and constant term. Cluster-robust errors in parentheses. Significance levels: *** 0.01, ** 0.05, * 0.1.

Table A11: Hours Absent: shift-work classification

	All			High			Low		
	Sickness absences	Paid leave	Unpaid leave	Sickness absences	Paid leave	Unpaid leave	Sickness absences	Paid leave	Unpaid leave
After	-7.922***	3.583***	-0.732	-7.375***	5.809***	1.100*	-8.070***	2.769**	-1.376*
	(0.310)	(1.079)	(0.688)	(0.447)	(0.855)	(0.615)	(0.335)	(1.178)	(0.762)
Sickness	0.149***	-0.269***	-0.235***	0.182***	-0.140***	-0.127***	0.143***	-0.302***	-0.265***
	(0.0110)	(0.0380)	(0.0251)	(0.0132)	(0.0366)	(0.0234)	(0.0121)	(0.0414)	(0.0286)
After × Sickness	-0.183***	0.376***	0.323***	-0.208***	0.164***	0.189***	-0.179***	0.440***	0.370***
	(0.0111)	(0.0336)	(0.0262)	(0.0141)	(0.0308)	(0.0180)	(0.0124)	(0.0391)	(0.0306)
Observations	14,253,940	14,253,076	14,245,396	3,144,660	3,144,514	3,141,398	11,109,280	11,108,562	11,103,998
Adjusted R^2	0.031	0.295	0.354	0.024	0.305	0.348	0.033	0.294	0.359

Notes: The table shows three sets of regression results (Equation 1). We divide the observations into quartiles (based on the shift-work classification) and present results for all observations in the 1st three columns, those in the top quartile (columns 4-6), and those up to the 75th percentile (columns 7-9) separately. We measure the sickness by counting the number of weeks with epidemic status in a quarter, using the incidence of influenza among children. The dependent variables are: sickness-related absences (sickness absence), paid and unpaid leave. Controls include: age, tenure, gender, collective agreement, quarter, year, county, industry, occupation, firm size cat., educ. cat., nationality. Cluster-robust errors in parentheses. Significance levels: *** 0.01, ** 0.05, * 0.1.

Table A12: Hours Absent (by occupations differently Exposed to Disease or Infections)

	All			High			Low		
	Sickness absences	Paid leave	Unpaid leave	Sickness absences	Paid leave	Unpaid leave	Sickness absences	Paid leave	Unpaid leave
After	-7.215***	3.311***	-1.434***	-5.877***	7.908***	1.084*	-7.551***	2.232*	-2.012***
	(0.334)	(1.181)	(0.521)	(0.676)	(1.027)	(0.584)	(0.362)	(1.347)	(0.567)
Sickness	0.131***	-0.277***	-0.236***	0.183***	-0.183***	-0.163***	0.120***	-0.289***	-0.242***
	(0.0119)	(0.0459)	(0.0281)	(0.0197)	(0.0503)	(0.0373)	(0.0127)	(0.0530)	(0.0300)
After × Sickness	-0.168***	0.369***	0.331***	-0.208***	0.139***	0.147***	-0.156***	0.424***	0.374***
	(0.0129)	(0.0359)	(0.0244)	(0.0233)	(0.0514)	(0.0279)	(0.0140)	(0.0409)	(0.0276)
Observations	6,027,004	6,026,560	6,024,372	1,309,800	1,309,596	1,309,434	4,717,204	4,716,964	4,714,938
Adjusted R^2	0.032	0.298	0.360	0.029	0.232	0.259	0.034	0.319	0.392

Notes: The table shows three sets of regression results (Equation 1). We divide the observations into quartiles (based on the O*NET classification) and present results for all observations in the 1st three columns, those in the top quartile (columns 4-6), and those up to the 75th percentile (columns 7-9) separately. We measure the sickness by counting the number of weeks with epidemic status in a quarter, using the incidence of influenza among children. The dependent variables are: sickness-related absences (sickness absence), paid and unpaid leave. Controls include: age, tenure, gender, collective agreement, quarter, year, county, industry, occupation, firm size cat., educ. cat., nationality. Cluster-robust errors in parentheses. Significance levels: *** 0.01, ** 0.05, * 0.1.

Table A13: Hours Absent (by occupations with different Contact With Others)

	All			High			Low		
	Sickness absences	Paid leave	Unpaid leave	Sickness absences	Paid leave	Unpaid leave	Sickness absences	Paid leave	Unpaid leave
After	-7.215***	3.311***	-1.434***	-4.291***	6.484***	0.213	-7.794***	2.398*	-1.923***
	(0.334)	(1.181)	(0.521)	(0.491)	(1.034)	(0.511)	(0.376)	(1.266)	(0.559)
Sickness	0.131***	-0.277***	-0.236***	0.169***	-0.176***	-0.166***	0.122***	-0.293***	-0.246***
	(0.0119)	(0.0459)	(0.0281)	(0.0182)	(0.0441)	(0.0343)	(0.0132)	(0.0507)	(0.0303)
After × Sickness	-0.168***	0.369***	0.331***	-0.169***	0.0742*	0.156***	-0.166***	0.443***	0.374***
	(0.0129)	(0.0359)	(0.0244)	(0.0194)	(0.0399)	(0.0231)	(0.0146)	(0.0394)	(0.0274)
Observations	6,027,004	6,026,560	6,024,372	1,251,616	1,251,533	1,251,324	4,775,388	4,775,027	4,773,048
Adjusted R^2	0.032	0.298	0.360	0.025	0.261	0.282	0.034	0.310	0.384

Notes: The table shows three sets of regression results (Equation 1). We divide the observations into quartiles (based on the O*NET classification) and present results for all observations in the 1st three columns, those in the top quartile (columns 4-6), and those up to the 75th percentile (columns 7-9) separately. We measure the sickness by counting the number of weeks with epidemic status in a quarter, using the incidence of influenza among children. The dependent variables are: sickness-related absences (sickness absence), paid and unpaid leave. Controls include: age, tenure, gender, collective agreement, quarter, year, county, industry, occupation, firm size cat., educ. cat., nationality. Cluster-robust errors in parentheses. Significance levels: *** 0.01, ** 0.05, * 0.1.

Table A14: Hours Absent (by occupations with different Social Orientation)

	All			High			Low		
	Sickness absences	Paid leave	Unpaid leave	Sickness absences	Paid leave	Unpaid leave	Sickness absences	Paid leave	Unpaid leave
After	-7.215***	3.311***	-1.434***	-4.907***	5.351***	-0.537	-7.725***	2.654**	-1.738***
	(0.334)	(1.181)	(0.521)	(0.520)	(1.043)	(0.495)	(0.369)	(1.275)	(0.573)
Sickness	0.131***	-0.277***	-0.236***	0.170***	-0.211***	-0.187***	0.122***	-0.284***	-0.241***
	(0.0119)	(0.0459)	(0.0281)	(0.0176)	(0.0452)	(0.0320)	(0.0131)	(0.0507)	(0.0307)
After × Sickness	-0.168***	0.369***	0.331***	-0.185***	0.116***	0.185***	-0.163***	0.435***	0.368***
	(0.0129)	(0.0359)	(0.0244)	(0.0194)	(0.0420)	(0.0234)	(0.0145)	(0.0393)	(0.0277)
Observations	6,027,004	6,026,560	6,024,372	1,310,676	1,310,587	1,310,395	4,716,328	4,715,973	4,713,977
Adjusted R^2	0.032	0.298	0.360	0.028	0.266	0.290	0.034	0.309	0.382

Notes: The table shows three sets of regression results (Equation 1). We divide the observations into quartiles (based on the O*NET classification) and present results for all observations in the 1st three columns, those in the top quartile (columns 4-6), and thosev up to the 75th percentile (columns 7-9) separately. We measure the sickness by counting the number of weeks with epidemic status in a quarter, using the incidence of influenza among children. The dependent variables are: sickness-related absences (sickness absence), paid and unpaid leave. Controls include: age, tenure, gender, collective agreement, quarter, year, county, industry, occupation, firm size cat., educ. cat., nationality. Cluster-robust errors in parentheses. Significance levels: *** 0.01, ** 0.05, * 0.1.

Table A15: Hours Absent: job-cell size interaction

	Adults' outbreak			Children's outbreak		
	Sickness absences	Paid leave	Unpaid leave	Sickness absences	Paid leave	Unpaid leave
Sickness	0.478***	0.167**	-0.283***	0.0563**	-0.229***	-0.153***
	(0.151)	(0.0818)	(0.0721)	(0.0230)	(0.0195)	(0.0161)
After*Sickness	-0.00352	0.706*	0.908***	-0.105***	0.523***	0.417***
	(0.555)	(0.407)	(0.280)	(0.0287)	(0.0268)	(0.0203)
Sickness*Size	0.0441	-0.104***	-0.0586***	0.0213***	-0.0404***	-0.0512***
	(0.0390)	(0.0252)	(0.0219)	(0.00659)	(0.00574)	(0.00469)
After* Sickness*Size	-0.129	-0.0172	-0.0514	-0.0124	0.00911	0.0146**
	(0.164)	(0.128)	(0.0867)	(0.00888)	(0.00912)	(0.00647)
Observations	310,945	310,945	310,945	310,945	310,945	310,945
Adjusted R2	0.101	0.486	0.557	0.101	0.490	0.560
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variables are average absence hours (sickness-related absences, paid and unpaid leave) in job cells. The sickness variable counts the number of weeks with epidemic status in quarter using the incidence of influenza among children. Controls include: indicator of periods after the reform and its interaction with the size of job-cells, age, tenure, gender, collective agreement, quarter, year, county, occupation, firm size cat., educ. cat., nationality, job-cell fixed effects. Cluster-robust errors in parentheses. Significance levels: *** 0.01, ** 0.05, * 0.1.

Abstrakt

Systém zdravotního pojištění je důležitý pro vybalancování ekonomických a zdravotních dopadů infekčních nemocí. Většina literatury zabývající se reformami zdravotního pojištění k odhadu dopadů změn překvapivě nevyužívá variaci v intenzitě, s jakou jsou pracovníci vystaveni nakažlivým nemocem. Porovnáním rozdílů v nemocnosti, tj. potřeby zdravotního pojištění, v českých okresech, zkoumáme efekty zavedení karenční doby na absenci pracovníků vystavených chřipce. Naše odhady na datech ISPV ukazují, že zavedením karenční doby se u pracovníků vystavených chřipce celková absence nezměnila, změnila se však její struktura. Pracovníci začali více využívat placenou a neplacenou dovolenou na úkor nemocenské. Výsledky dále naznačují, že zavedením karenční doby se nezměnila míra šíření nákazy na pracovišti.

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